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Review

State-of-the-Art of Artificial Intelligence and Big Data Analytics Reviews in Five Different Domains: A Bibliometric Summary

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Abstract: Academicians and practitioners have recently begun to accord Artificial Intelligence (AI) and Big Data Analytics (BDA) significant consideration when exploring emerging research trends in different fields. The technique of bibliometric review has been extensively applied to the AI and BDA literature to map out existing scholarships. We summarise 711 bibliometric articles on AI & its sub-sets and BDA published in multiple fields to identify academic disciplines with significant research contributions. We pulled bibliometric review papers from the Scopus Q1 and Q2 journal database published between 2012 and 2022. The Scopus database returned 711 documents published in journals of different disciplines from 59 countries, averaging 17.9 citations per year. Multiple software and Database Analysers were used to investigate the data and illustrate the most active scientific bibliometric indicators such as authors and co-authors, citations, co-citations, countries, institutions, journal sources, and subject areas. The USA was the most influential nation (101 documents; 5405 citations), while China was the most productive nation (204 documents; 2371 citations). The most productive institution was Symbiosis International University, India (32 documents; 4.5%). The results reveal a substantial increase in bibliometric reviews in five clusters of disciplines: (a) Business & Management, (b) Engineering and Construction, (c) Healthcare, (d) Sustainable Operations & I4.0, and (e) Tourism and Hospitality Studies, the majority of which investigate the applications and use cases of AI and BDA to address real-world problems in the field. The keyword co-occurrence in the past bibliometric analyses indicates that BDA, AI, Machine Learning, Deep Learning, NLP, Fuzzy Logic, and Expert Systems will remain conspicuous research areas in these five diverse clusters of domain areas. Therefore, this paper summarises the bibliometric reviews on AI and BDA in the fields of Business, Engineering, Healthcare, Sustainable Operations, and Hospitality Tourism and serves as a starting point for novice and experienced researchers interested in these topics.

Keywords: artificial intelligence; AI; big data; deep learning; neural networks; NLP; fuzzy logic; expert systems; big data analytics; big data analysis; I4.0; bibliometric analysis

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1. Introduction

The fourth Industrial Revolution (I4.0) brought out many disruptive technologies that have substantially transformed existing systems and brought up new business models and processes across diverse domains and sectors [1–3]. Alongside, decision-making has increasingly been decentralized to computer systems, notably with the dawn of Artificial Intelligence (AI) and Big Data Analytics (BDA) [4]. AI mimics human intelligence and cognitive abilities with the assistance of machines or computers [5–7]. Colson [8] and Lichtenthaler [9] contend that AI can make decisions that are sometimes superior to those made by humans. Big Data refers to the enormous volume of data that cannot be managed and processed by conventional data management methods [10]. BDA refers to analyzing such massive datasets to emanate actionable insights and value [11–13]. Executing AI and BDA delivers a competitive edge to an organization with tangible growth prospects in its social and corporate status [14]. It is now possible to derive actionable insights from the billions of datasets sired every minute using AI-powered tools [15]. AI, Machine Learning (ML), and supporting BDA are growing at an unprecedented rate, opening up preposterous opportunities to enrich the performance of various industries, research capabilities, and businesses.

In line with the UN SDG#12 goal of achieving sustainable production and consumption through scientific, innovative and technological capabilities, Di Vaio, Palladino, Hassan and Escobar [5] emphasized the applications of AI in sustainable business models (SBMs). To achieve sustainable growth and development in a disruptive environment, many organizations have already started adapting to AI and/or other tech-driven solutions [5,16]. Di Vaio, Boccia, Landriani and Palladino [1] demonstrate how AI has been applied in the sustainable agri-food industry and their supply chains (AI for sorting of food, supply-chain optimization, food security, hygiene standard, and food and drink preparations). Abdollahi, et al. [17] compile literature and exhibit how wireless networking devices can improve agricultural activities. By connecting UN SDG #3 (Healthy lives and well-being for all), Liao, et al. [18] show how BDA and visualization can be applied in medical research to achieve sustainable healthcare. In a similar line, Morato, et al. [19] show the recent sustainable technologies for older adults to promote healthy ageing and the social inclusion of the elderly using a smart environment. Cano, et al. [20] show how open innovation, e-market places, and sustainability are inter-connected from sustainable logistics using I4.0 and big data environment. Similarly, Giuffrida, et al. [21] explored the literature on last-mile logistics optimization techniques and found that machine learning techniques and mixed methods are widely used in sustainable or smart logistics. On the other hand, Samuel, et al. [22] demonstrated how digital technologies would have significant environmental impacts due to high carbon dioxide emissions associated with the energy consumption required to generate and process large amounts of data; mineral extraction for, and manufacturing of, technological components; and e-waste. Loureiro and Nascimento [23] identified that AI, IoT, circular economy, BDA, AR, and VR emerged as major trends in tourism research, broadening our understanding of how technology can shape the future of sustainable tourism.

Chen, Chiang and Storey [4] also argue that 'Technological Intelligence,' the capacity to relish and adapt to technological advancements, is compulsory for all businesses. The machine-readable data furlough and steadily rising computation power and storage capacity have significantly impacted many sectors. Hence, businesses must dig through the scope of AI and BDA applications and map out their apparent vulnerability to disruptions. So far, many domains have opened up to AI applications over the past decade. Such applications include AI, ML, and Deep Reinforcement Learning (DRL) for Smart city and sustainable operations [1,24,25]; Supply chain management [26]; Medical diagnosis and treatment [3,27]; Pandemic response and prediction modelling [28,29]; Dentistry [30]; Engineering and constructions safety [31]; Power quality assurance [32]; Commercial banking and stock market predictions [33,34]; Enhanced marketing and customer experience [35], and many others. Similarly, BDA, with various AI algorithms, improved computing power and cloud storage, improved decision-making quality and added new value to various fields. These emerging fields of BDA study include smart logistics and IoT [36], precision agriculture and smart farming [37,38]; sustainable architecture [39]; consumer analytics and marketing transformation [40] and many diverse areas.

Technological changes are dynamic and progressing at a rapid rate. More businesses are capitalizing on their technological edge to accomplish superior performance and competitive advantage in a tech-driven world [6]. In the past decade, a 'variety' of large data sets have been generated at high 'velocity', resulting in the development of pristine AI-driven data processing tools. In chorus, BDA also saw exponential growth. Many companies, including Netflix, Google, Airbnb, Amazon, Adidas, and Uber, have already adopted AI technologies due to the competitive business vortex and the necessity for real-time decision-making [38,41,42]. Wiener, Saunders and Marabelli [10] argue that many companies have begun overhauling their business models or developing new ones—giving rise to the 'big-data business model' phenomenon. For instance, Lufthansa Air has successfully concocted business value by exploiting Big Data available [43]. In, et al. [44] argue that "alternative data" that does not fall under the purview of traditional company fundamentals, security prices, and macroeconomic indicators garner an increasing interest amongst finance professionals. Such structured and unstructured ESG data types include audio recordings, written articles, social media posts, satellite images, etc. They point out that such ESG big data sources now significantly influence investment decisions. The trend of AI and BDA adoption, digital transformation, and workforce upskilling by various industries has garnered the attention of academics and practitioners [45].

Numerous scholarly works investigate the applications of AI and BDA in various fields. Researching the application of AI and BDA concepts without reviewing their performance in a timely manner would not produce tangible results. Consequently, it is essential to evaluate the state of AI and BDA research in different fields. This bibliometric study intends to examine influential and well-cited bibliometric reviews on AI and BDA written by eminent researchers from various fields. Any significant academic work starts with a thorough literature review. Therefore, we contend that extensive bibliometric reviews indicate extensive academic research in these fields. Thus, we examine all bibliometric works published in these two interrelated fields to date. We also conduct a bibliometric analysis of bibliometric review papers written on AI and BDA in order to determine the current state of the field. The study primarily aims to recapitulate the recent direction of academic research on AI and BDA. We posed the ensuing research questions: How many impactful bibliometric reviews have been published on AI and BDA in different fields over the past decade? Which are the leading authors, institutions, journals, domain areas, and nations conducting bibliometric reviews on AI and BDA across various fields? What are the most influential reviews, prominent topics, and themes emerging on AI with its subsets and BDA in various fields? Which are the most promising areas where AI and BDA have so far been applied to? This bibliometric study of past bibliometric articles seeks to identify the most productive authors, institutions, top contributing countries, subject-area, influential authors, and journals that performed bibliometric reviews of articles published in the Scopus Database.

We contribute to the literature by identifying five distinct research clusters of discipline that engage in extensive research on AI and BDA and proposing future research directions. This article would be a "one-stop-shop" of bibliometric reviews in the five primary areas of research: Business and Management, Engineering and Construction, Healthcare, I4.0, sustainable operations, and Tourism research. It also shows the temporal and geographical distribution of publications; most popular publication platforms; salient keywords, applications & use cases, and emerging topics. We also update managers about the latest applications of AI and BDA to enable them to harness the benefits of using AI and BDA for all five research areas.

The paper is organized as follows. Section 2 briefly recalls the conceptual background of AI & its sub-domains and BDA, while Section 3 explains the methodology, tools, and data. Section 4 analyses our bibliometric result expands them with content analyses, and Section 5 concludes our study.

2. Theoretical Background

This section provides a comprehensive explanation of AI and its components, Big Data Analytics, and the semantics associated with them.

2.1. Artificial Intelligence (AI)

AI is the philosophy of machines to think, behave and perform the same or similar to humans [46]. It was introduced at the Dartmouth Conference in 1956 [47]. Since then, it has been a profound technology and has brought unparalleled success through speech recognition, image classification, reasoning, machine translation, and information retrieval [47]. AI uses a computer to emulate intelligent human behavior with the least amount of human participation possible [48]. In simple terms, AI is when a machine can reason, solve problems, and learn. For example, AI engine algorithms can now recognize new objects they have not seen before. It is typically characterized as a machine's ability to learn from experience and new inputs and carry out tasks like a human being [49]. Figure 1 exhibits a brief history of AI and its season using [14,50].

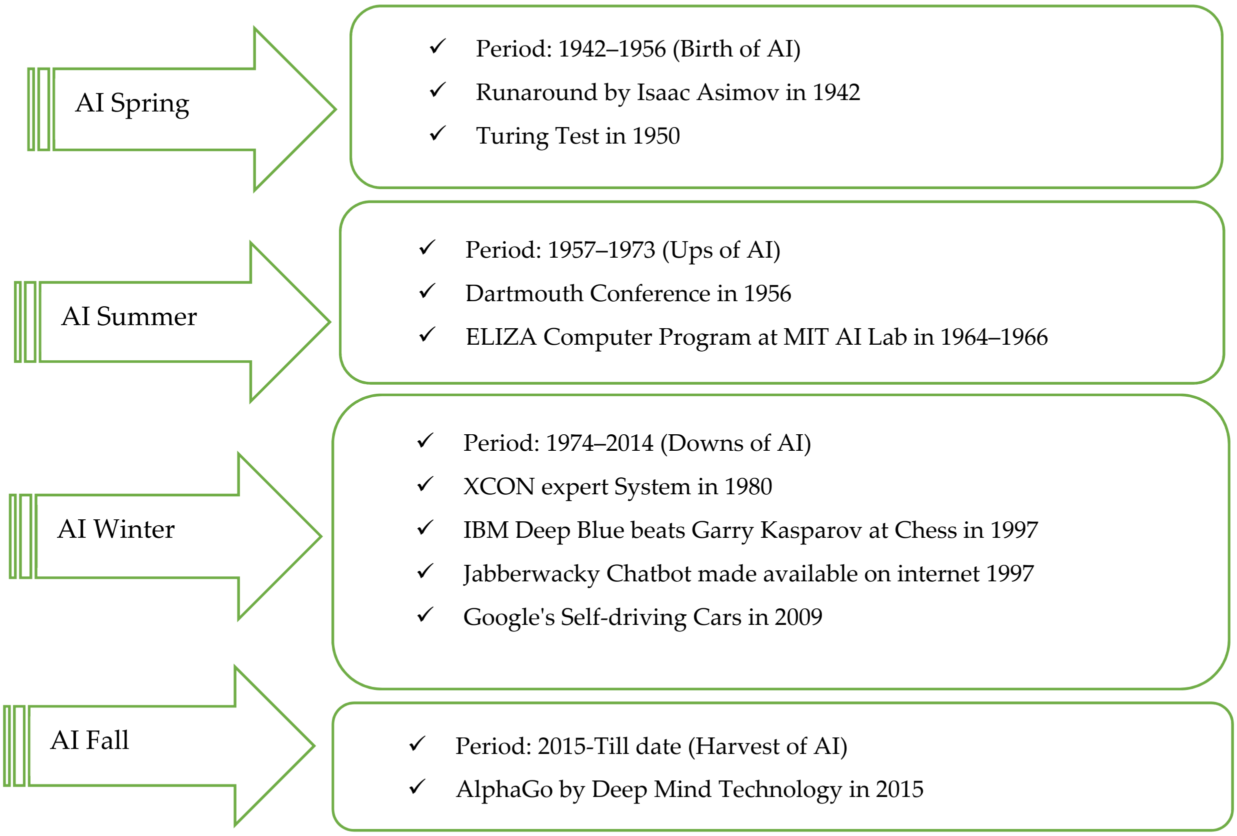

Figure 1. Brief History of AI: Compiled from Haenlein and Kaplan [50] and Wamba, Bawack, Guthrie, Queiroz and Carillo [14].

Based on the past literature, AI is defined as the science of making intelligent machines [49]; a machine that can model human behavioral patterns [26]; a set of technologies that can surpass human learning and problem-solving [51]; a machine with experience and intuition [52]; a sub-set of IT that senses, understands, learns, and acts on data interpretation [53]; an algorithm that performs perceptual, cognitive and interaction functions [5]. Simply, it is a system that uses human-like intelligence [27].

2.1.1. Stages in AI Evolution: AI Evolution Has Three Phases

(1) ***Artificial Narrow Intelligence (Weak AI):*** Intelligence devoted to assisting with or taking over only specific tasks—e.g., Siri, Alexa, Cortana, and Self-driving Cars are examples [54].

(2) ***Artificial General Intelligence (Strong AI):*** Machines will own the capacity to think and make judgments like human beings [55]. We have not yet arrived at this stage of AI development. However, researchers are optimistic that we will soon be able to get to this point.

(3) ***Artificial Super Intelligence*:** It is a stage of AI wherein computers will surpass human beings [56]. As of now, this stage of evolution is considered a hypothetical scenario.

AI continues to develop, and its applications are endless. With time and technology, once-essential AI functions like Character Recognition are now assumed to be inherent to systems. AI can now be used to improve product performance, make quicker and more informed decisions, develop new products, optimize internal operations, and automate jobs [45,57] and new markets can be explored, and sales and marketing can be optimized with AI [7]. Some narrow AI applications include self-driving cars, detecting banking fraud, estimating stock prices [34,58], computer gaming, drug dosage, and surgical procedures [59]. Several jobs are being automated, and it is thus commonly believed that AI will impact the future of work too [45]. Self-driving cars may soon replace human drivers and taxis [60]. In general, we anticipate that the responsible application of AI will enhance our lives. A common criticism, however, is that AI systems and algorithms are only as smart as humans if trained by humans and given high-quality data. Human bias cannot be kept out of the operation of AI systems and their results [61,62]. Therefore, humans should know that machines learn from experience using probabilistic modelling and optimized artificial decision-making capabilities [63]. The role of AI in achieving sustainable business models has already gained traction in the literature. In parallel, numerous industries continue to adopt AI-driven business solutions and models alongside (for example; see Di Vaio, Palladino, Hassan and Escobar [5]).

Advances in AI and its subsets, such as Machine Learning, Deep Learning (DL), and BDA, can lead to many breakthroughs in biology, transportation, I4.0, e-commerce, finance, education, NLP, and computer vision and imaging. Studies have identified the advantages of applying AI technologies to Big Data problems and the significant value of analytical insights and predictive capability for various problems [10]. BDA and AI can even predict epidemic outbreaks like Blue Dot, a Toronto-based start-up that uses an AI-based surveillance system to detect COVID-19 well ahead of the Chinese authorities [29]. Big data and AI are complementary. Dwivedi, et al. [64] note that Big Data and its integration with AI have garnered significant attention in the academic literature. AI is utilized in BDA to improve data analysis. Consequently, AI requires vast data to learn and enhance decision-making processes.

2.1.2. Branches of AI

Depending on the problems, the domains of AI tasks are classified into three. They are formal, mundane, and expert problems [64]. The well-known sub-domains or branches of AI are given in Table 1:

Table 1. Branches of Artificial Intelligence and Applications.

	It is the science of programming a machine to interpret, process, and analyse data to solve real-world problems [33]. Three types of learning fall under this category: (a) supervised learning, (b) unsupervised learning, and (c) reinforcement learning. For example, a Machine Learning algorithm can predict stock price index movements [11,34]. Lin, et al. [65] showed how a random forest ML algorithm (supervised) model can be used for evaluating risk for an excavation system. Support Vector Machines (SVM) is another algorithm for supervised machine learning that can be applied to classification and regression problems [66].
	It is the process of executing neural networks on high-dimensional data to gain insights and form solutions [67]. The neural network is the logic behind the face verification algorithm on Facebook and Self-driving Cars, and Virtual assistants like Siri and Alexa. Extensive research is currently being conducted on the applications of deep learning in healthcare to improve the quality of diagnosis [68]. Deep Learning has been applied to interpret the remote sensing images [69]; precision agriculture [37].

Table 1. *Cont.*

	NLP is the science of drawing insights from human language to communicate with machines [70]. Twitter uses NLP to filter out terrorist languages in their tweets, and Amazon uses NLPs to review customer feedback and user experience [71]. NLP is also increasingly utilized in medical research [72]. Mäntylä, et al. [73] show the applications of NLP tools, sentiment analysis by text mining, topic modelling, and latent Dirichlet Allocation to understand product reviews. Such sentiment analysis has been applied in stock market buying decisions, elections, disasters, medicine, software engineering, and cyberbullying.
	The branch of AI focuses on the different applications of robots. AI robots are artificial agents which act in the real-world environment embarking on some accountable actions. Sophia, a social humanoid robot, is the best example of AI Robotics. Google's LaMDA, Open AI's GPT-3, and Meta's BlenderBot are some of the example's AI-based conversational chatbots created out of massive data language models [74]. Care-robotics for elderly support is another application of robotics [75]. Robotic Process Automation modules that build, deploy, and manage software robots that emulate humans actions interacting with digital systems and software are widely used in auditing [57].
	A computing approach is based on the tenet of the degree of truth rather than Boolean logic, which is "true or false." Fuzzy logic is extensively used in the medical field, involving complex problems and decision-making [65]. Fuzzy logic is also used in automating gear systems in cars. For instance, Fuzzy logic can be applied to identify Periodontal disease and candidiasis risk factors in dentistry [30].
	It is an AI-based computer system that learns and reciprocates the decision-making ability of human experts [76]. It employs the 'if-then' logic notion to solve any complex problems. They do not rely on conventional procedural programming. They have seemed to be used in fraud detection, information management, virus detection, and managing medical and hospital records. A good example is the XCON Expert System of the 1980s, which automatically chooses and orders computer parts based on what the customer wants [14].

2.2. Big Data

Digital data has outgrown traditional systems and methods [77]. Big data is everywhere, and data-driven discovery is a new computing paradigm [78]. Big Data is a term that refers to large amounts of structured and unstructured data that can be used to extract relevant information [10]. Gupta and Rani [77] point out that data capture, data storage, data manipulation, data management, data analysis, knowledge extraction, security, privacy, and are flooded with opportunities and difficulties as data grows. Emails and multimedia contents shared on different social media platforms alone generate countless gigabytes of data [49,79,80]. In simple, big data signify a new era in data exploration and data utilization for creating value [81]. By characteristics, big data is an enormous volume of data that cannot be managed using conventional data management techniques [82]. Big Data typically retains five characteristics: variety (diversity), velocity (real-time), volume (amount), veracity (quality), and value (worth) [13]. It remains an abstract term as new dimensions continue to be added over time. Many new features have been added to the definition of Big Data. As seen in Figure 2, Big data now has 8Vs: Volume, Velocity, Value, Variety, Variability, Validity, Viscosity, and Veracity [39].

There are numerous distinctions between Traditional Data and Big Data in terms of their characteristics [83]. Traditional Data is expressed in gigabytes, whereas Big Data is always updated in terabytes and petabytes. Traditional data generation is measured in hours per day, whereas Big Data has been generated rapidly [84]. Traditional data is always in a structured format, while Big Data is always semi-structured or unstructured [49]. Traditional Data is stored centrally, but Big Data is completely distributed. Such traditional data can be integrated using a relational database management system. In contrast, it is impossible with Big Data [78,85]. Such Big Data can be accessed interactively in batch or near real-time. Traditional data is primarily utilized in transactional contexts and is unorthodox in big data. Analysing such a massive amount of big data and concluding it presents a significant challenge [83]. As per Bendre and Thool [83], some of the important challenges, as well as unique features of Big Data, are:

(a) Heterogeneous, Inconsistent, and Incomplete data
(b) Confidentiality, Expendability, and Energy Management
(c) Transmission, Curation, Analysis
(d) Scaling, Data Privacy, and Timeliness
(e) Analytical Mechanism, Visualization, and Collaboration.

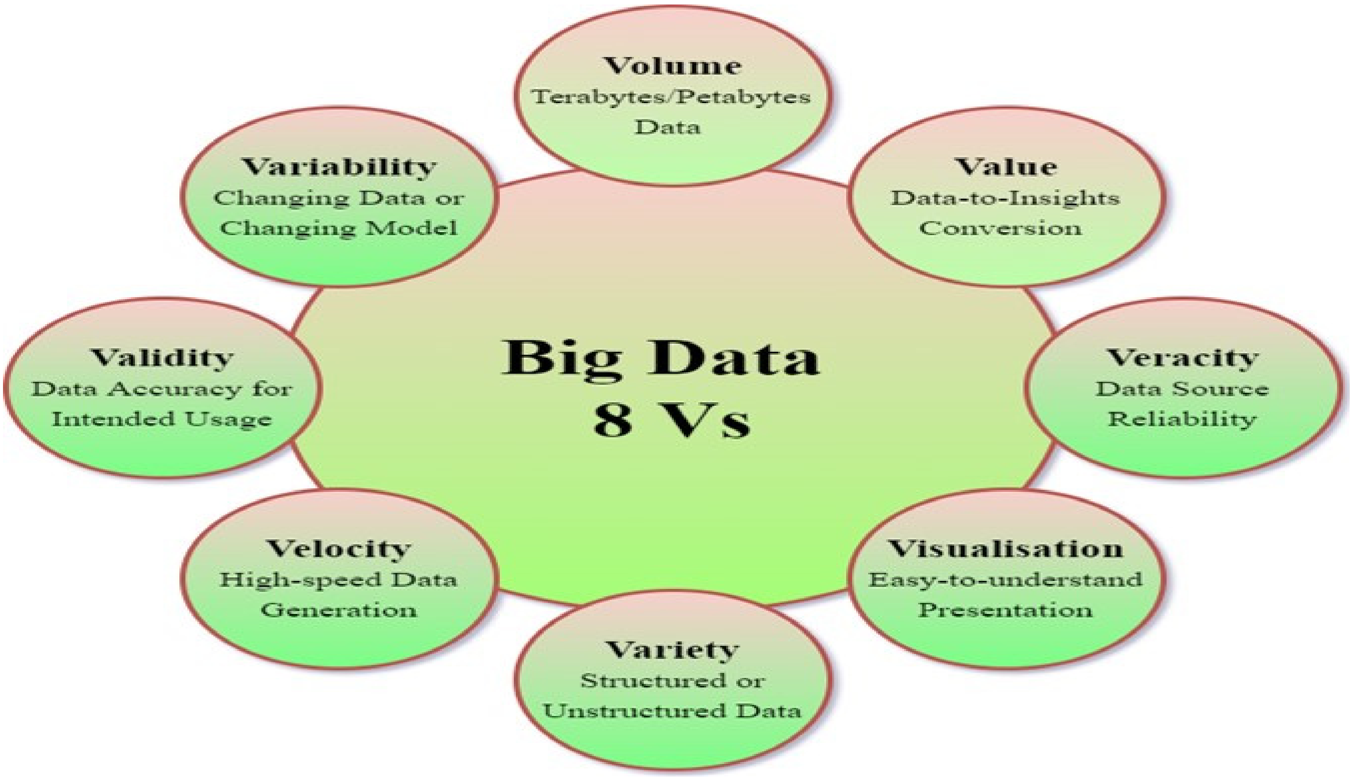

Figure 2. Eight Vs of Big Data.

2.2.1. Big Data Analytics (BDA)

The analysis of such enormous datasets to derive actionable insights and value is known as Big Data Analytics [11,12]. Batistič and van der Laken [12] view that with more computational power, machine learning—specifically deep learning via neural networks—has become more widely utilized by businesses. The method of extracting value from BDA was pioneered by firms in technology-intensive industries [86]. It encompasses various data-intensive methods capable of analysing massive amounts of data [13]. The success of BDA determines whether the user employs big data to make impactful or informed decisions and make a 'big' impact [4]. It contributes significantly to decision-making processes because large-scale data have high granularity—detailed information related to a study objective. In general, the BDA contains the following steps:

1. ***Data Generation*** from audio-visuals, the internet, sensors, and real-time applications. For example, Twitter generates billions of tweet-related data monthly [71].
2. ***Data Acquisition*** involves collecting, pre-processing, and transforming data for applications. Big data acquisition gathers, filters, and cleans large datasets. The sensor network is widely used to collect data from various static and dynamic applications e.g., wireless sensors network in precision agriculture [17].
3. ***Data Storage*** is made on clustered server platforms and community hardware. Some firms employ big data cloud models and systems [83]. For instance, GoogleFS is a distributed file system for big data generation applications [87]. Hadoop Distributed

File Systems (HDFS) and Kosmos File Systems (KFS) are open-source products of GoogleFS. MapReduce is a programming model and enabler for underlying numerous big data platforms for the distributed and scalable processing of big data [88]. In certain circumstances, a sensor-integrated RFID data repository approach employing MongoDB stores IoT-generated data is also used [89].

4. ***Data analytics*** extracts insights from large datasets using ML and data mining techniques. BDA inspects knowledge for decision-making and involves finding hidden patterns, connections, and relationships [83]. Knowledge retrieved can improve customer service, sales, decision support, and knowledge bases. Recently, a CIM-based visual data mining system was presented to facilitate query-driven analysis of large utility data [25]. Large-data analysis requires distinct methodologies, strategies, and procedures. Structured data analytics, text analytics, web analytics, multimedia data analytics, mobile analytics, and network analytics are some types of BDA [9].
5. ***Data Visualization*** of large data sets is meaningfully visualized using statistical software packages such as R studio, Matlab, etc. Numerous organizations have created their own visualization tools for the graphical representation of data. For example, GIS-based 3D visualization systems may import city building models, resident information, traffic data, etc. [90]. FinaVistory uses narrative visualization to visualize social and financial news linkages [91].

Bendre and Thool [83] warn that Return on Investment (ROI) from such BDA is an additional concern as BDA involves enormous data storage and processing power costs. However, the declining costs of data collection stimulated the widespread application of BDA in numerous industries. The applications of analytics on big data are vast. By following the contributions of Bendre and Thool [83], some of the applications of BDA in different fields are listed below:

2.2.2. BDA in Healthcare

Healthcare data growth is exponential, and most medical data is unstructured [83]. Usually, big medical data are generated in both structured and unstructured texts, multimedia, and hypertext formats [83]. Extracting insights from medical diagnosis data such as EMRs, X-ray and CT scans, laboratory documents, reference notes, claims reports, CRM systems, and biomedical machinery is a big challenge [92]. The advantage of applying data mining to big data in health informatics is that the software and statistical tools are now available for handling big data problems such as high dimensionality and class imbalance [93]. Thus, the healthcare industry must implement medical BDA to establish a viable health informatics system affordable to patients. Using statistical and bio-statistical approaches helps analyze patient records [3]. The current ML algorithms and techniques help healthcare to find insights from the historical and real-time data generated by various healthcare components [33,93]. Medical BDA requires analysing healthcare system data and frequent testing before use [94]. AI subsets such as machine learning [18], deep learning via a neural network [68], and NLP [72] are widely used to derive insights from big medical data. BDA would help improve individual and genomic medicine, drug safety, disease diagnosis, improved treatments, and patient outcomes.

2.2.3. BDA in Government

The government's various programmes, facilities, and services to its citizens are one of the biggest data sources [92]. These data come from the police, transport, defense, national security, agriculture, revenue, environmental, social, and security departments [83]. BDA can extract knowledge and insights from available data to improve policy implementation [95]. BDA extends help in defence, crime recording, police surveillance, tracking terror threats, and crime graphs [96]. The main aim of government is to seek benefit by utilizing IoT, crowdsourcing, and data sources and encourage public talent by creating enterprise partnerships. The primary obstacles for the government are data ownership, data quality, civil rights, and the diverse BDA needs of the business sectors. The assistance after the 2010

Haiti earthquake highlights how big data may aid life-critical services [83]. In addition, Hashem, Chang, Anuar, Adewole, Yaqoob, Gani, Ahmed and Chiroma [81] show how effectively BDA can be used to manage smart cities.

2.2.4. BDA in Banking

The applications of BDA in the Banking Sector have been revolutionizing services and enhancing security [97]. The BDA applications may include developing a customer-focused organization, optimizing risk and security management and offerings, and cross-selling while increasing flexibility and streamlining the processes. Further, BDA may also help understand the needs of customers and employees and provide improved quality and service management techniques [98]. The banks acquire the data using text that would help the banks come up with customized offers about bank loans, interest rates, and bank accounts to enhance customers' retention and satisfaction [99]. Banks gather data from different sources and are combined, verified, enhanced, and processed using various BDA approaches, alongside meeting the need for data transmission and data integration. Using BDA, the standstill and failed banking transactions may also be avoided using statistical approaches and work scheduling with parallel and distributed processing. By applying iCARE software (developed by IBM for analysing big data on consumer behaviour) with BDA models, banks would know the specific needs of customers and satisfy the same by coming up with solutions [67].

2.2.5. BDA in Insurance

In the insurance industry, insurance companies also face difficulties in anticipating consumer perceptions and needs while introducing a new product [100]. To create and offer lucrative insurance policies, BDA helps forecast customer behavior, needs, and interest. Policymakers can easily forecast future insurance policies using predictive models and machine learning techniques [101]. Since the major goal of insurance firms is to offer dependable services and achieve the utmost customer satisfaction, text and web mining techniques may help obtain the web-based data gathered from a wide range of sources, including policy agents, websites, social media, phone records, and user-interactive systems and facilitate the more accurate prediction of customers' needs [102]. Real-time prediction of consumers' behaviour through BDA helps insurance companies launch make customer-centric insurance products and make more penetrative marketing strategies. Through the application of BDA, this analytical and predictive approach of the insurance companies may assist them in forecasting the behaviour of the customers and enable them to achieve customer satisfaction [101].

3. Data and Methodology

3.1. Data Source

As emulated in many previous bibliometric reviews [34,103], we gathered our data from the Scopus Database (see File S1 at Supplementary Materials). We used this database for a variety of reasons. First, it is one of the largest multidisciplinary academic literature databases that have been peer-reviewed Donthu, Kumar, Mukherjee, Pandey and Lim [15]. Second, it is among the best accessible databases encompassing the most reputable journals in various disciplines. Thirdly, it delivers users with advanced search capabilities and a variety of bibliometric analysis tools, such as the ability to export need-based bibliographical data and search result visualization.

3.2. Keyword Selection & Refinement

To guarantee precision, we followed two primary phases for the keyword selection. In phase one, we investigated online dictionaries and lexicons for AI and BDA to identify the most relevant keywords. In the second phase, we executed a two-step Scopus advanced search for AI and its subsets and BDA. The initial search phase was exploratory. We used the Scopus keyword feature to add more terms to our final advanced query. To proceed to Stage 2, we reviewed each keyword and search results individually.

Table 2 shows the search criterion and article selection steps we followed for analysis. An advanced search was conducted using the TITLE, ABSTRACT, and KEYWORD criteria following the preparation of the query. To access standard bibliometric articles for the scope of our study, we restricted the results to "Articles", "Conference Papers", and "Reviews" in English-medium journals, yielding 1190 documents. We also conducted multiple online refinements. AI and BDA bibliometric reviews were in the single digits before 2010. Hence, we restricted the articles, conference papers, and reviews to the years 2012–2022. Second, only Scopus Q1 and Q2 quality criteria were used to filter the journals. In addition to using manual filtration techniques to eliminate irrelevant articles, we examined the relevance of each paper to the topic. This inclusion and exclusion criterion depended on the topic's explicit coverage within the defined field of literature. The 711 bibliometric reviews that remained after the filtration process were used for additional bibliometric and content analyses. Specifically, these are all AI and AI-subsets-related bibliometric reviews published in Scopus Q1 and Q2 journals of different subjects.

Table 2. Search criteria and article selection.

Filtering criteria	Accept
Database	Scopus
Search date	23 October 2022
Period: 2012–2022	1201
Query strings: (TITLE-ABS-KEY ("Artificial Intelligence" OR "AI" OR "Big data" OR "Machine Learning" OR "Reinforcement Learning" OR "neural network*" OR "Deep Learning" OR "Expert Systems" OR "Natural Language Processing" OR "NLP" OR "Robotics" OR "Fuzzy Logic" OR "Big Data Analytics") AND TITLE-ABS-KEY ("Bibliometric Analysis" OR "Bibliometric Review*" OR "Bibliometric Study"))	1230
Article type: Articles, Conference Papers, and Reviews	1105
Source type: Journal	878
Language screening: Only paper written in the English language	843
Scopus Q1 and Q2 (As per Scopus Ranking 2021)	711

3.3. Study Approach and Tools

Bibliometric analysis is useful for established and emerging scholars who want to review broad and rich research areas [15]. Pritchard [104] was the first person to present the idea of using bibliometrics as a method for determining and grasping the network of published articles that are based on citations. Donthu, Kumar, Mukherjee, Pandey and Lim [15] provide detailed guidelines on how to conduct (a) Performance Analysis, (b) Science Mapping, and (c) Network Analysis for Bibliometric Analysis. Bibliometric analysis owns a superior ability to produce accurate results providing readers with all-inclusive information about intellectual, conceptual, and social structures on a particular topic [105]. Analysis of journals, subjects, themes and topics, countries, universities, and output of authors are some of the other applications of Bibliometrics [106].

First, we did a performance analysis using the relevant scientific indicators identified from prior studies. Second, we conducted a citation analysis to reveal the performance of various scientific indicators (i.e., documents, authors, journals, affiliations, and countries). Third, we carried out a network analysis and science mapping by employing VOSviewer and RStudio (Biblioshiny) to carry out the keyword co-occurrence, factorial Analysis, trend analysis, co-authorships, and bibliographic coupling [107]. In this particular instance, we used VOSviewer [12]. Both programs are utilized extensively in the investigation of bibliometric information A summary of the research design is presented in Figure 3 below:

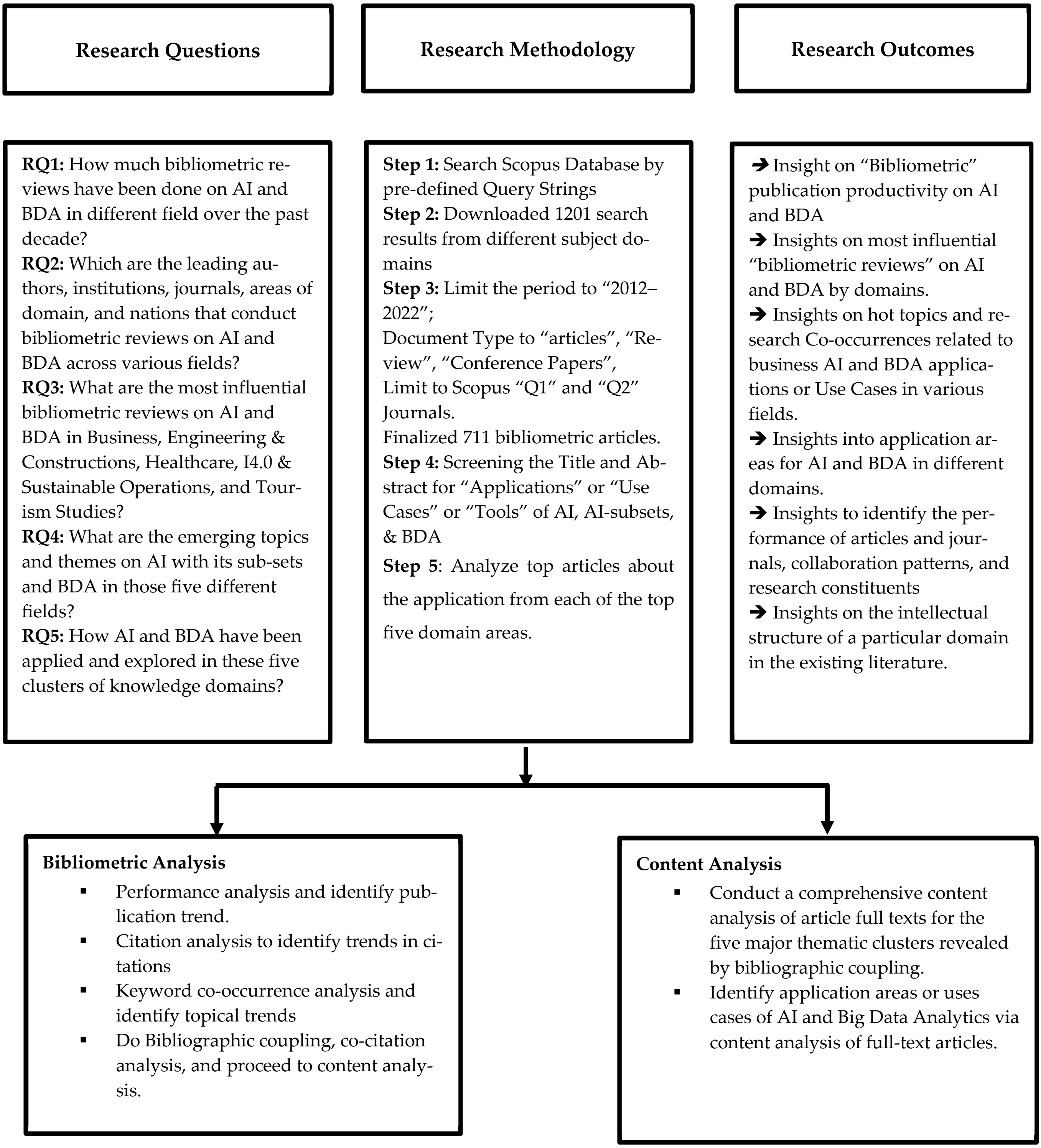

Figure 3. Research design and scheme of analysis.

4. Results and Discussions

4.1. General Information and Performance Analysis

As per Table 2, our dataset included 711 bibliometric articles published in 423 journal sources between 2012 and 2022. The average number of citations per document was 17.9, while the documents' average age was only one year and three months. In addition, 2334 authors were identified from 711 different bibliometric review articles. Authors of 711 reviews have used 1900 distinct keywords to best describe their work. In addition, the authors cited approximately 47722 sources in the review articles they published in Scopus Q1 and Q2 journals.

Figure 4 illustrates the frequency distribution of publications growth from 2012 through 2022. The bibliometric review article growth attained an annual production growth rate of 65.21%. It's worth noting that research output remained almost constant between 2012 through 2018. But significant growth began in 2019. This trend is expected to intensify over the next decade as India and China. Other nations have begun to explore AI and BDA in different fields. 2022 is the most active year with 303 documents, followed by 2021 with 192 records and 2020 with 106 papers in bibliometric reviews of AI and Big Data research. Remember, we retrieved 2022 data on 23 October, and there are two more months left in 2022. The bibliometric reviews on AI and BDA published in different journals show an exponentially increasing trend. It is also evident that bibliometric analysis of the topics under study fast-tracked post-COVID-19.

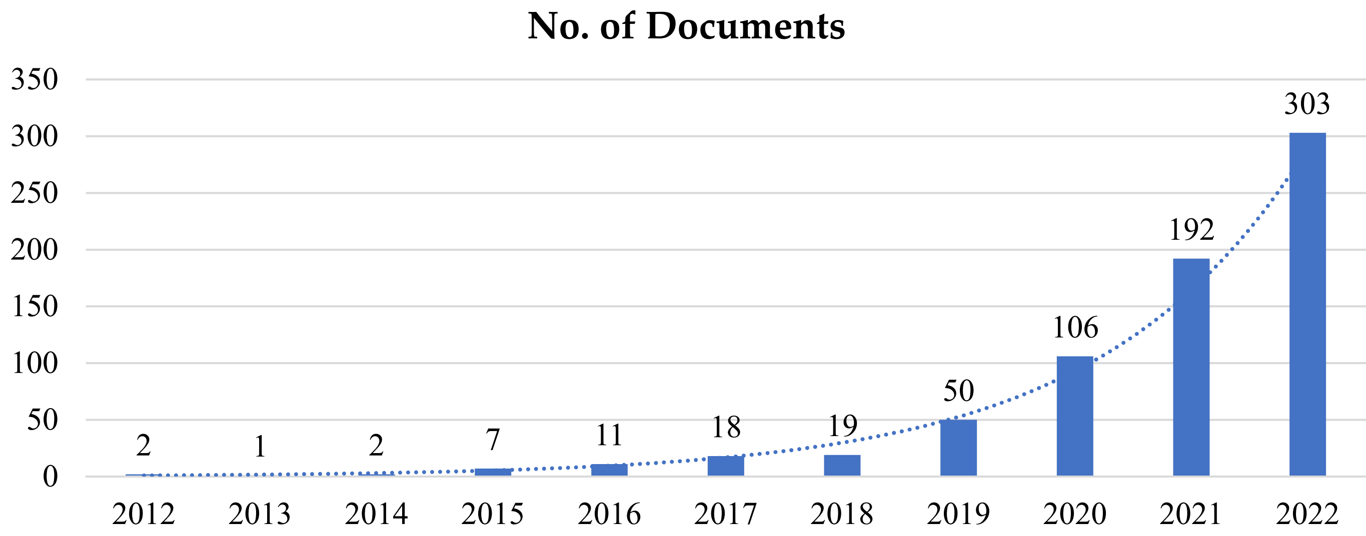

Figure 4. AI and BDA Bibliometric Review Growth.

Figure 5 depicts the top ten influential bibliometric review contributing countries in different fields. We discovered that the United Kingdom, China, the USA, India, and Malaysia are the five most productive and influential nations. To clarify, we counted a country as productive and influential if at least one author is affiliated with a local institution in a country. For instance, if four authors from the United States, the UK, India, and China collaborated on a bibliometric article, each country will be credited once. Due to the intrinsic limitation of this approach, we also relied on the respective authors for additional information regarding national productivity. Figure 6 depicts the frequency of the most active countries by corresponding authors. Additionally, the ratios of Multiple Country Publications (MCP) to Single Country Publications (SCP) are provided.

The most active and relevant research institutions/affiliations in bibliometric review contribution is exhibited in Figure 7. This information is helpful for identifying funding organizations, early-career researchers, potential collaborators, and students seeking research and post-graduate programs in AI and BDA-related fields. The top three active research institutions are Symbiosis International Deemed University, India (including Symbiosis Institute of Technology, Pune), with 32 Scopus Q1 or Q2 bibliometric articles. Chinese Academy of Science, China published 14 bibliometric reviews on AI or BDA, followed by Malviya National Institute of Technology, Jaipur, India, which published 12 articles employing bibliometric analysis. In India, Symbiosis International University (Private Deemed) contributed the most bibliometric reviews, whereas Public Universities in China contributed the majority of reviews. It indicates that the Chinese Government has already started to fund and promote impactful research in AI and BDA areas.

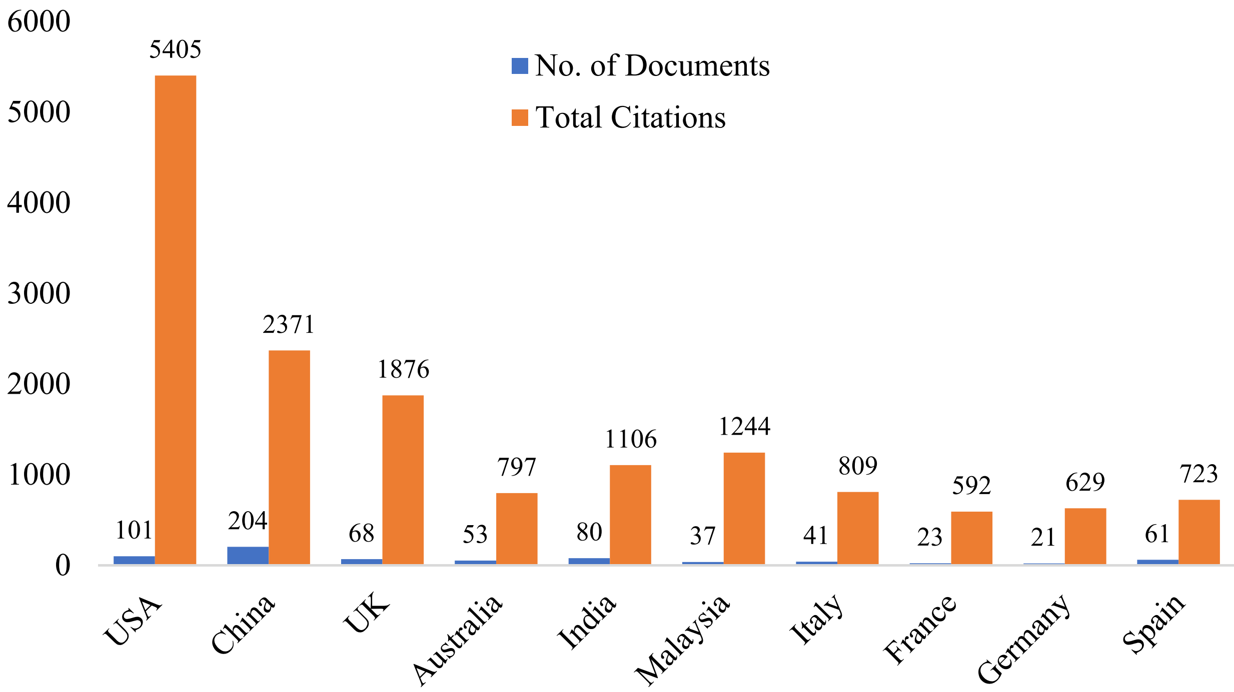

Figure 5. Top ten productive and impactful countries.

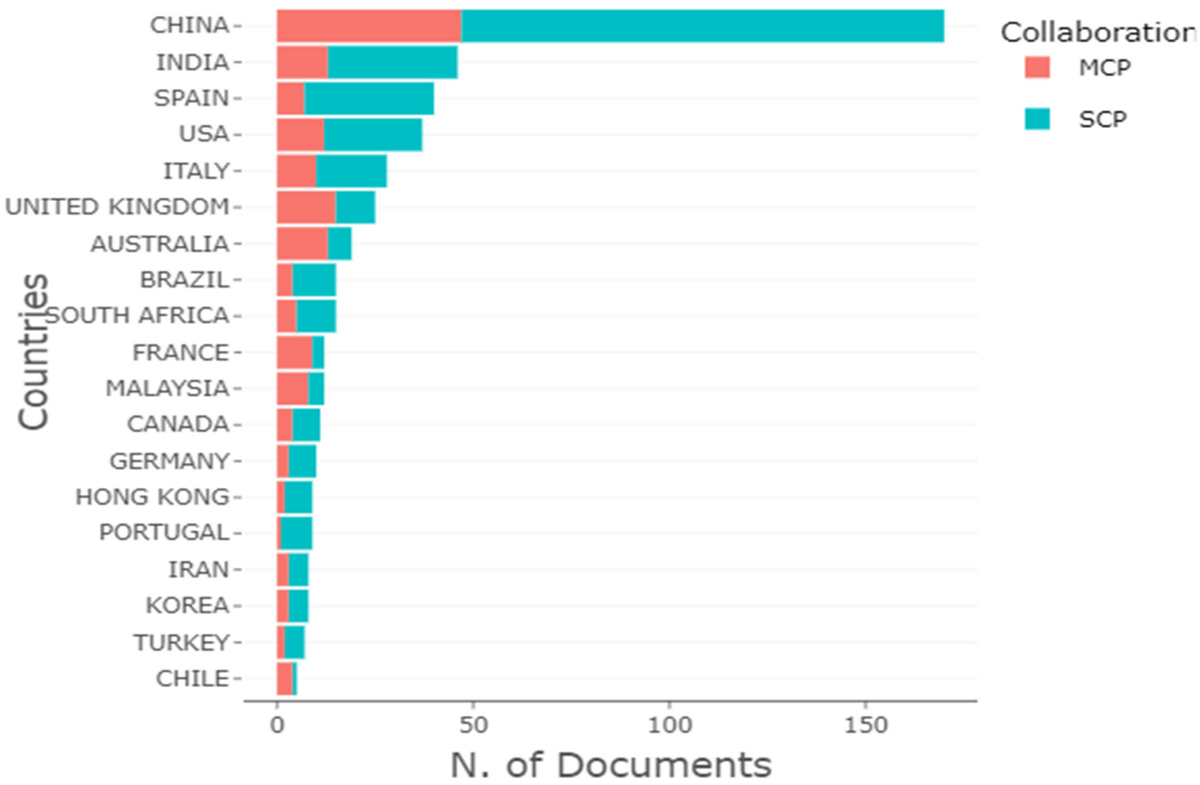

Figure 6. Country Production based on Corresponding Authors. Note: MCP = Multiple Country Publications; SCP = Single Country Publications.

4.2. Citation Analysis

Citation analysis determines the frequency of citations and is used to rank journals and scholars and assess their scientific impact [108]. As a result, citation analysis might reveal information about an article's popularity. Despite some objections, it continues to be used within a study field for assessing and determining significant authors, journals, papers, and countries [13].

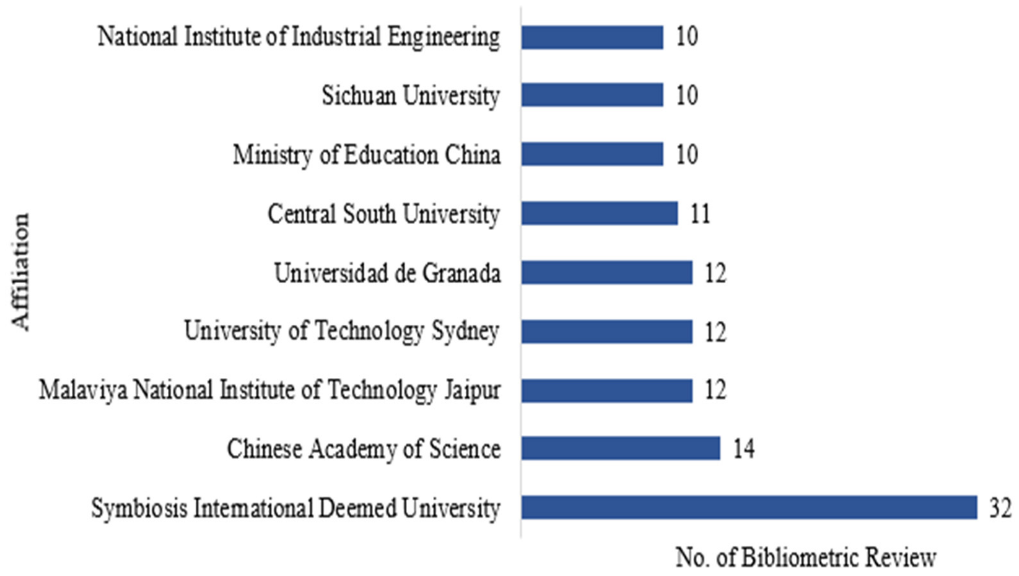

Figure 7. Most Active Academic Institutions.

Table 3 displays the top 10 authors and their respective number (frequency) of publications and affiliations. By 18 October 2022, Professor Xieling Chen (TC = 170; H = 6; G = 10; M = 1.2) of The Education University of Hong Kong published eight bibliometric reviews exploring the applications of AI and its sub-sets (viz. NLP, text mining, and computing) in Educational Technology and Medical Research. Professor Haoran Xie (TC = 119; H = 5; G = 8; M = 1) from Lingnan University, Hong Kong, contributed seven bibliometric analyses in a similar area of NLP applications in medical research and AI in technology-enhanced learning.

Table 3. Top Ten Productive Authors.

Name	Scopus ID	Affiliation(s)	PYS	TLS	NP	TC	H	G	M
Chen, Xieling	57031196900	The Education University of Hong Kong, Hong Kong	2018	1406	10	170	6	10	1.2
Kumar, Satish	57202477277	Malaviya National Institute of Technology, Jaipur, India	2021	931	8	104	5	8	2.5
Xie, Haoran	57219619828	Lingnan University, Hong Kong	2018	1351	8	119	5	8	1
Lim, Weng Marc	57193912670	Sunway University, Bandar Sunway, Malaysia	2021	767	7	99	5	7	2.5
Xu, Zeshui	55502698400	Sichuan University, Chengdu, China	2019	931	7	143	5	7	1.25
Kotecha, Ketan	6506676097	Symbiosis International University (Deemed), Pune	2021	206	6	23	3	4	1.5
Cheng, Garry	35995385400	The Education University of Hong Kong, Hong Kong	2019	1575	5	49	3	5	1
Cobo, Manel J.	25633455900	UGR Granada, Spain	2019	713	5	175	3	5	0.75
Kumar, Anil	57001679600	London Metropolitan University, London, United Kingdom	2021	853	4	22	3	4	1.5
Abraham, Ajith	7202760099	Machine Intelligence Research Labs, Auburn, United States	2019	253	4	315	4	4	1

Note: PYS = Publishing Year Starting; **NP** = Number of Publications; **TC** = Total Citations; **H** = H-Index; **G** = G-Index; **M** = M-Index; **TLS** = Total Link Strength.

Professor Satish Kumar (TC = 104; H = 5; G = 8; M = 2.5) from Malaviya National Institute of Technology, Jaipur, India, is the second best-published author with eight bibliometric articles. He extensively reviewed the use cases of AI and its subsets, particularly in the fields of accounting information, personalized marketing, AI and blockchain integration in business and finance. His reviews concentrated primarily on AI and its applications in accounting, finance, and business. Similarly, Professor Manel Jesus Cobo Martin (TC = 175; H = 3; G = 5; M = 0.75) from UGR Granada, Spain, carried out five bibliometric reviews across various disciplines such as AI Models in business and management, opinion mining, sentiment analysis, and emotion understanding in advertising, fuzzy-logic based decision making, decision-making using IoT and ML, etc. Professor Lim Weng Marc (TC = 99; H = 5; G = 7; M = 2.5) of Sunway University, Bandar Sunway, Malaysia, has started publishing these areas in 2022 and has been impactful with his seven bibliometric articles. In 2022, he published articles on manufacturing-specific deep learning, conversational bots, personalized marketing, and BDA.

With only four bibliometric articles covering topics such as Industry 4.0, engineering applications of AI, fuzzy-technique applications in Big Data, etc., Ajith Abraham has become an impactful author. He received the most citations (315) among the top ten most productive authors. Whereas, Ketan Kotecha of the Symbiosis Institute of Technology in Pune, India, has published six bibliometric articles on AI, ML, DL, Multimodal AI, and Explainable AI in various fields, such as emotion detection for textual Big Data, Smart Wearables, Incremental Clustering, etc. in Scopus Q1 or Q2 journals. Although he has published more, the impact of these articles is relatively meagre in number. Figure 8 depicts the article production activity of ten influential authors since 2018.

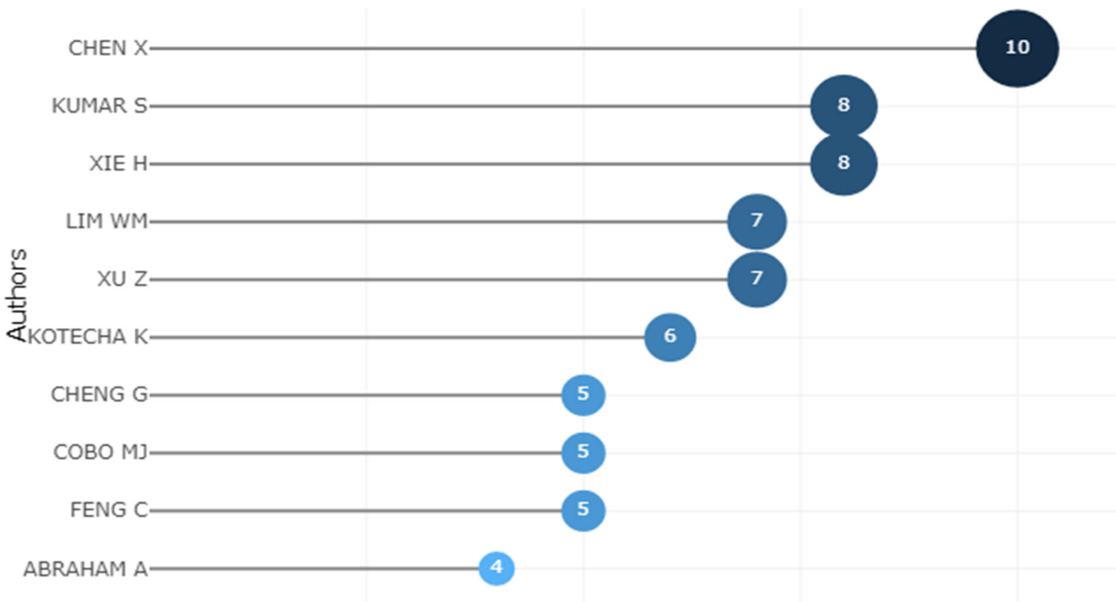

Figure 8. Top Ten Relevant Authors.

Table 4 shows the subject-wise most relevant academic sources that contributed to the influential bibliometric reviews on AI and/or BDA. First, *Sustainability* Journal published 41 bibliometric articles in multidisciplinary areas with a total citation of 532. Second, *Scientometrics* Journal, which predominantly publishes in library science and computer and information science, published 16 bibliometric articles with 425 over the past decade. *IEEE Access* also contributed 18 articles with 91 citations in Engineering, Computer Science, & Material Science areas. This information can aid researchers in identifying productive sources in various fields and locating relevant documents based on their specific areas of interest.

Finally, the most relevant research institutions or affiliations are presented in Figure 7. Figure 8 displays the most relevant authors with the highest number of bibliometric review contributions. We identified the top 10 most relevant authors published between 2012 through 23 October 2022.

Table 4. Subject-wise Influential Academic Sources (By number of Articles).

Sources	Articles **	Subject/Category	TC	H-Index *	Country
Sustainability	41	Energy, Environmental Science, Social Science	532	109	Switzerland
Scientometrics	16	Computer Science and Library Science	425	123	Netherlands
IEEE Access	18	Computer Science, Engineering, & Material Science	91	158	USA
Frontiers in Oncology	12	Medicine (Oncology) Biochemistry, Genetics, Molecular Biology	23	102	Switzerland
International Journal of Environmental Research and Public Health	13	Environmental Science & Public Health	74	138	Switzerland
Journal of Medical Internet Research	11	Medicine—Health Informatics	176	158	Canada
Automation in Construction	8	Engineering: Building & Construction	217	138	Netherlands
Expert Systems with Applications	7	Computer Science & Engineer	112	225	UK
Technological Forecasting and Social Change	8	Business, Management, & Accounting; Psychology	187	134	USA
Environmental Science and Pollution Research	6	Environmental Science & Medicine	40	132	Germany

Note: TC = Total Citations on the Articles published in the Journal. * As per Scimago Journal Ranking as of 16 October 2022, ** Numbers are shown after inclusion/exclusion criteria.

Figure 9 demonstrates that most bibliometric reviews on these topics first appeared in 2018. Satish Kumar, Weng Marc Lim, Zeshui Xu, and Manuel J. Cobo have significantly contributed to Business and Management. Zeshui Xu reviewed deep learning, support vector machines, applied intelligence, rough sets, and intelligent decision-making, whereas the three authors focused primarily on business and management topics. Ajith Abraham also has had a significant impact over the past four years. His bibliometric articles covered trending topics such as Industry 4.0, engineering applications of AI, fuzzy-technique applications in Big Data, etc.

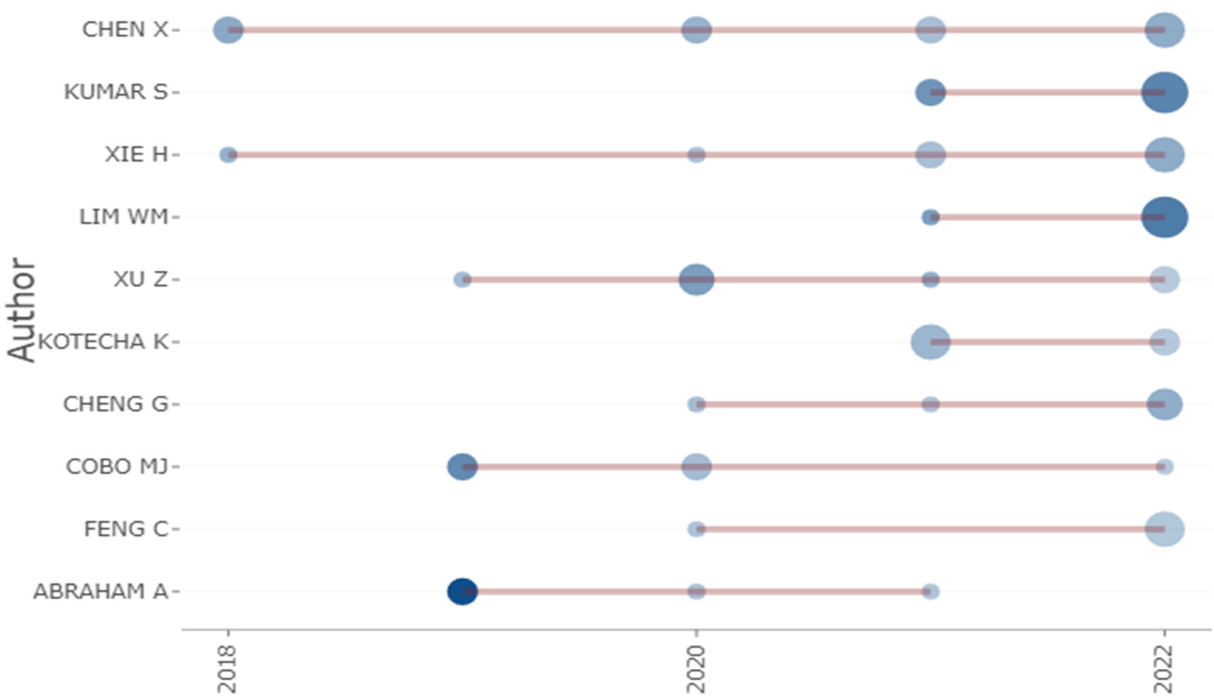

Figure 9. Productivity of Authors (Top ten authors over past four publishing years). Note: The circle grew as the author published more articles that year. The circle turns darker if the article(s) get more citations that year.

4.3. Influential Journals

The top 50 most impactful publications between 2012 and 2022 are shown in Table 7. Figure 10 shows the most highly cited academic sources throughout the past decade. *MIS Quarterly: Management Information Systems* earned the biggest influence with a single article published in 2012. The article "Business intelligence and analytics: From big data to big impact", published by MIS Quarterly, received the most citations, 3378. However, bibliometric review contributions on AI and BDA in this journal are relatively less. Similarly, the Computer Methods and Programs journal in Biomedicine has been a strongly influential journal with only three bibliometric documents published. As seen in Table 4, *Sustainability* and *Scientometrics* also have a significantly high number of publications and citations. *Engineering Applications of Artificial Intelligence, Computer Science Review, Automations in constructions, Technological Forecasting and Social Change, International journal of medical informatics, Journal of Medical Internet research, International Journal of Information Management, Annals of Operations Research, Journal of Business Research*, etc ... are some of the impactful journals that published a smaller number of bibliometric articles but received a relatively high number of citations.

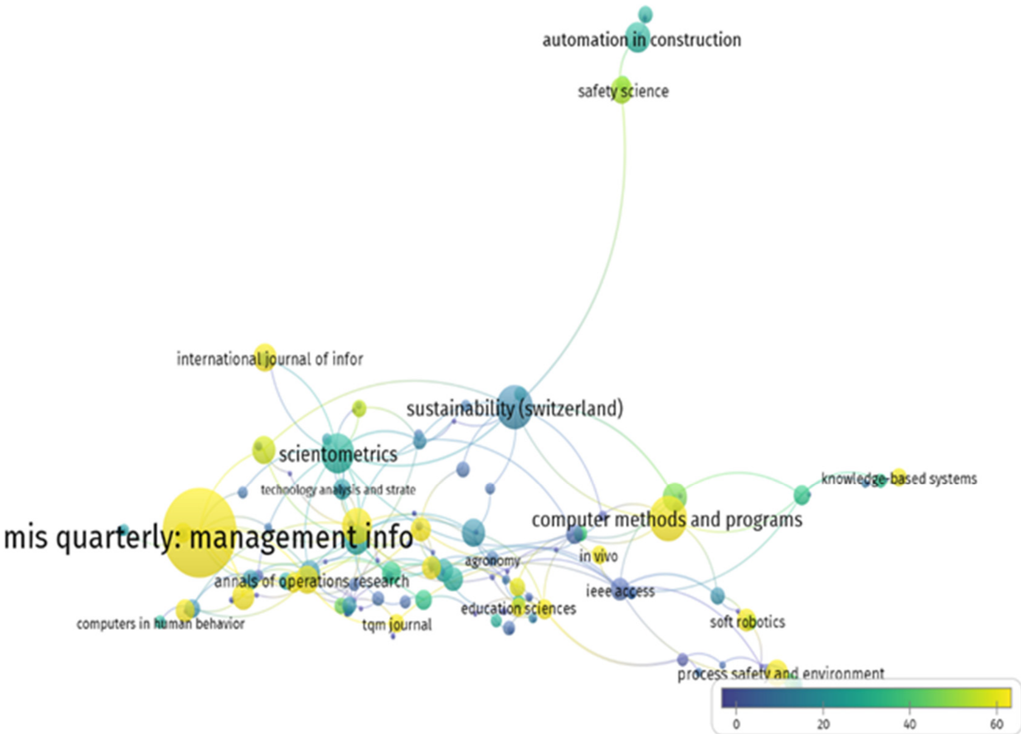

Figure 10. Influential Academic Source. Note: We assigned citations as weight, and the Influence score is calculated based on average citations.

4.4. Keyword Co-Occurrence Analysis

Figure 11 shows the author keyword co-occurrences in different bibliometric articles we compiled. We chose a minimum number of "three" keyword occurrences. The result returned 134 results meeting the threshold. Of which, certain most appeared generic keywords such as "Bibliometric Analysis", "Vosviewer", "Scopus", "Review", etc., are excluded to make the keyword analysis meaningful. Table 5 displays author keyword co-occurrences and total keyword link strength. As expected, 'Artificial Intelligence' accounted for the highest number of 115 occurrences, with the highest number of links established being 165. Its sub-set 'Machine Learning' also appeared nearly 105 times. 'Big Data' was mentioned 87 times in the author's keyword, followed by 'Deep Learning' 35 times, 'Sustainability' 30 times, and 'Industry 4.0′ occurred 28 times. Search results returned almost all relevant keywords, such as Big Data Analytics, NLP, IoT, Robotics, Latent Dirichlet Allocation, Topic Modelling, Fuzzy Logic, Emerging Technologies, and so forth.

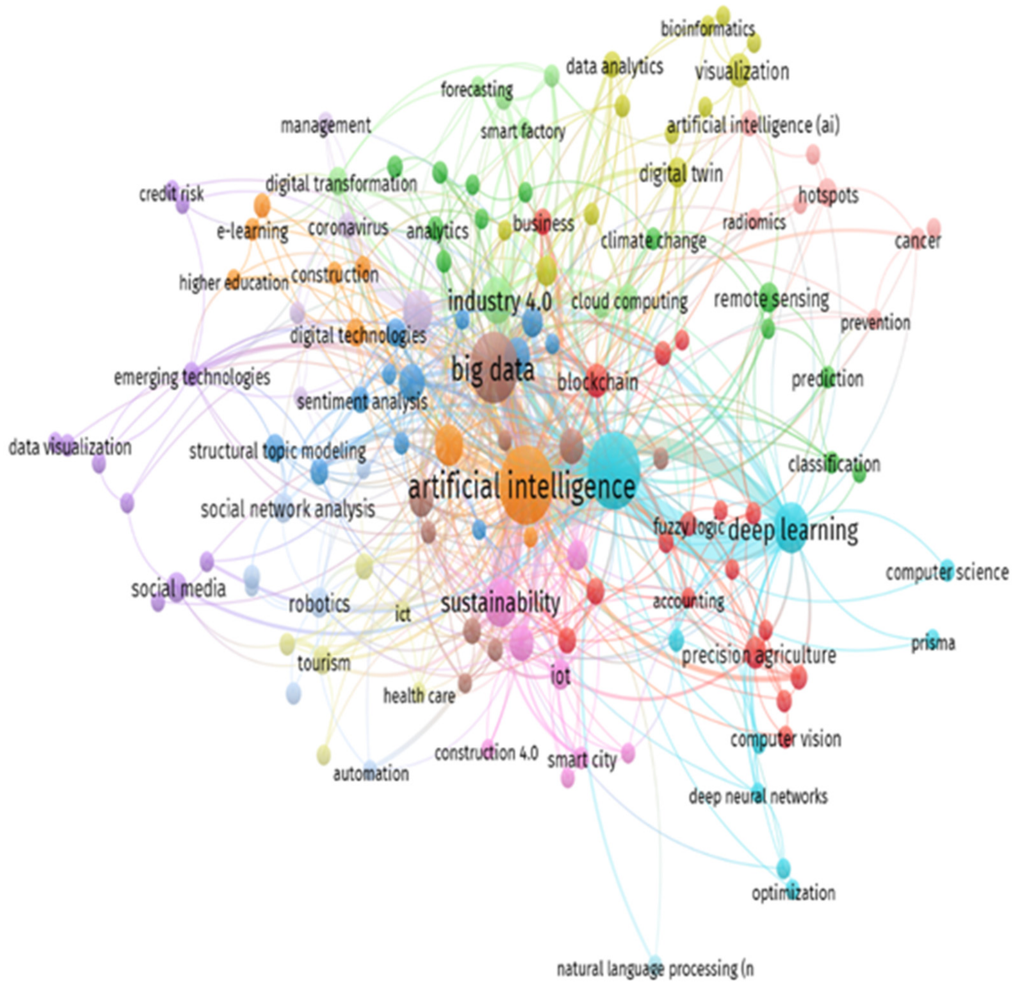

Figure 11. Keyword Co-occurrence. **Note:** The size of the nodes indicates the frequency of co-occurrence, while the curves between them indicate co-occurrence. More keywords co-occur when the nodes are closer. This figure helps identify content clusters.

Table 5. Author Keyword Co-occurrences and Links.

Keyword	Occurrence	Total Link Strength
Artificial Intelligence	115	165
Machine Learning	105	157
Big Data	87	132
Deep Learning	35	73
Sustainability	30	64
Industry 4.0	28	63
COVID-19	23	54
Big Data Analytics	19	35
Text Mining	16	26
Natural Language Processing	15	13
Internet of Things	14	37
Data Mining	13	21
Supply Chain Management	13	27
Visualization	12	8
Blockchain	11	29
Precision Agriculture	10	15
IoT	9	29

Table 5. *Cont.*

Keyword	Occurrence	Total Link Strength
Robotics	9	19
Social Network Analysis	9	13
Digital Twin	8	14
Healthcare	8	13
Latent Dirichlet Allocation	8	15
Remote Sensing	8	10
Social Media	8	7
Supply Chain	8	23
Cloud Computing	7	21
Digital Technologies	7	15
Digital Transformation	7	21
Hotspots	7	6
Structural Topic Modeling	7	8
Topic Modeling	7	11
Tourism	7	16
Artificial Intelligence (AI)	6	8
Business	6	11
Circular Economy	6	15
Coronavirus	6	17
Data Analytics	6	9
Innovation	6	8
Sentiment Analysis	6	11
Smart Cities	6	23
Sustainable Development Goals	6	17
Technology	6	13
Agriculture	5	12
Analytics	5	11
Education	5	6
Emerging Technologies	5	16
Fourth Industrial Revolution	5	14
Fuzzy Logic	5	3
Ontology	5	8
Robotic Surgery	5	3

4.5. Co-Authorship Analysis

Collaborations among authors from different countries and academic affiliations can improve research quality [13]. Co-authorship analysis investigates academic collaboration and intellectual exchange [108]. Co-authorship analysis, for example, can reveal clustered research among researchers in a particular field, and this information can be used to launch new research in under-researched areas and countries. The analysis also provides an understanding of collaboration across different time periods, providing prospective scholars with critical information to connect with research hotspots. Figure 12 depicts the distribution of co-authorship by country. We set the minimum number of documents to ‘one’ and the minimum number of citations per country to ‘twenty’ to narrow the search. As a result, the outcome revealed a pattern of collaboration involving 54 of 81 countries with decent link strengths. Nine clusters of co-authorship analysis by country demonstrate strong collaboration networks among scholars from various countries.

USA contributed 101 documents with 5405 citations and 117 Total Link Strength (TLS). Their average number of citations per document exceeds fifty. However, this high score is largely influenced by pioneering work on Big Data [4], which received over 3500 citations by itself. China has produced a significant number of 204 documents with 2371 citations. The United Kingdom is the third best country for collaboration, with 68 documents containing 1876 citations and 106 TLS. Malaysia is the fourth best country for collaboration based on citations, with 37 documents earning 1,244 citations and 72 links established. India is the fifth-best country for collaboration, with 80 bibliometric articles containing 1106 citations and 77 TLS in place. Numerous nations, including the Russian Federation, Qatar, Belgium, and Switzerland, did not collaborate on bibliometric research on AI and Big Data.

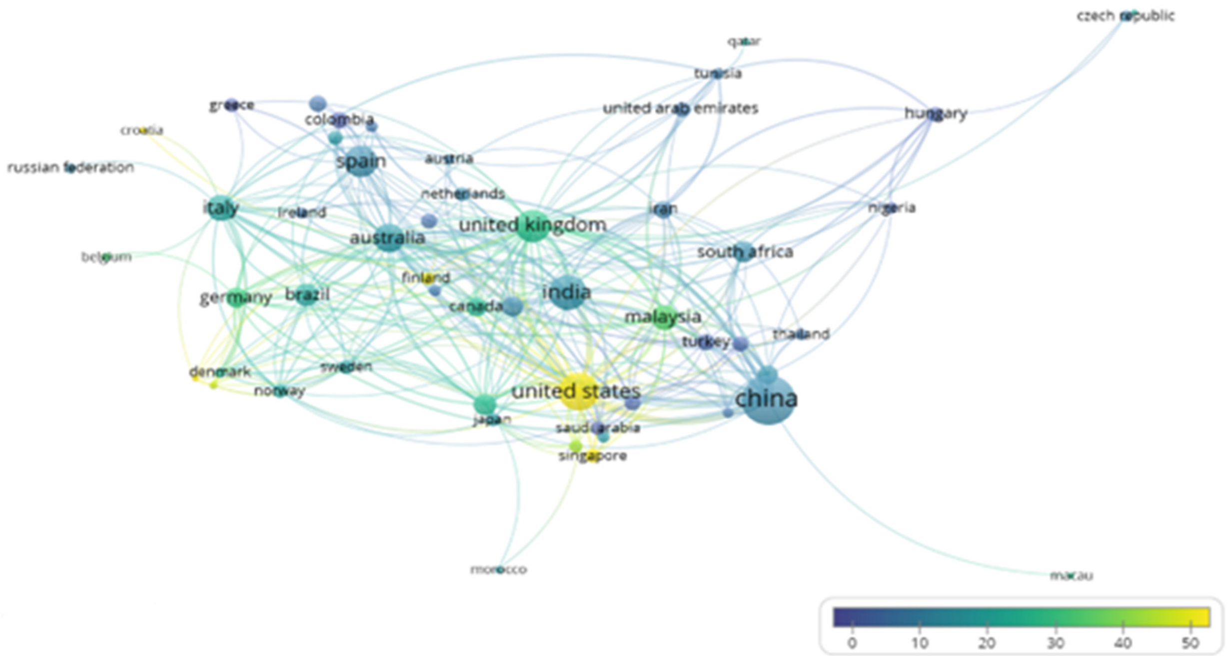

Figure 12. Overlay Visualisation of Co-authorship by Countries. **Note:** We assigned Citations as weight, and the Influence score is calculated based on average citations.

4.6. Bibliometric Coupling

This method of analyzing existing literature compares two works linked by a common document. The more references that are shared in both publications, the more similar their intellectual capital is. Citation chaining backwards is also used to evaluate the research topic [13]. The bibliometric coupling has previously been performed using various units of analysis, such as author, affiliations, countries, and journal sources [13]. As illustrated in Figure 13 and Table 6, we perform a bibliometric coupling by documents and recognize the top 20 authors with influential citations and strong links to other works.

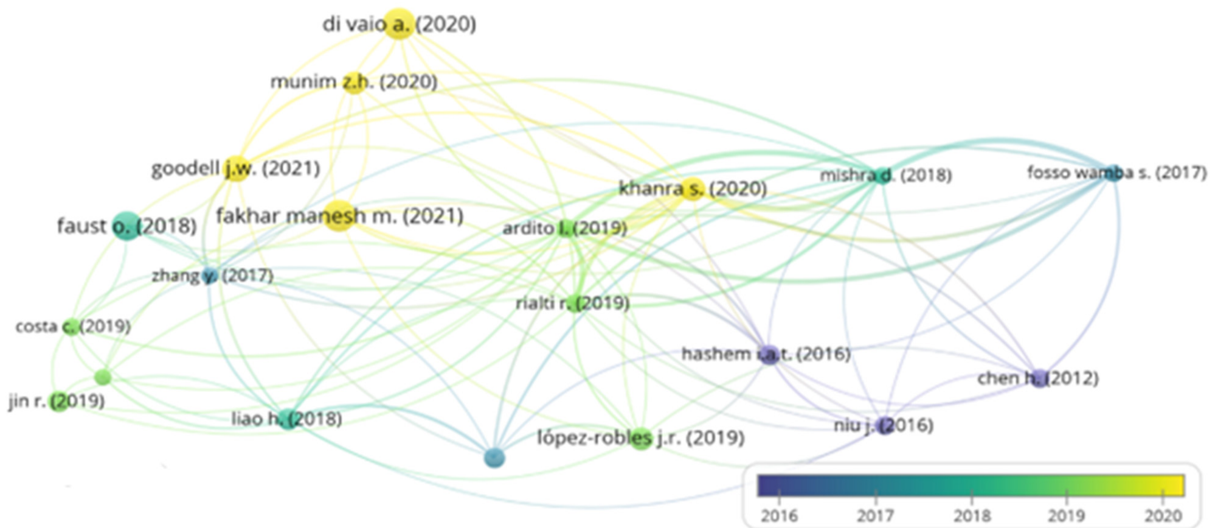

Figure 13. Overlay Visualisation of Bibliometric Coupling by Documents. **Note:** We assigned Citations as weight, and the Influence score is calculated based on Normalised citations. Minimum Citations: 50.

Table 6. Bibliometric Coupling by Documents.

Document	Citations	Total Link Strength
Chen, Chiang and Storey [4]	3378	13
Faust, Hagiwara, Hong, Lih and Acharya [68]	529	6
Liao, Tang, Luo, Li, Chiclana and Zeng [18]	284	22
Mishra, Gunasekaran, Papadopoulos and Childe [108]	252	73
Di Vaio, Palladino, Hassan and Escobar [5]	239	10
López-Robles, Otegi-Olaso, Gómez and Cobo [2]	196	13
Jin, et al. [109]	147	5
Gu, Li, Li and Liang [94]	143	17
Manesh, et al. [110]	141	13
Rialti, Marzi, Ciappei and Busso [82]	130	52

According to Table 6, the most influential author on business intelligence and big impactful data was Prof. Chen [4], who published about deep learning applications in healthcare. Liao, Tang, Luo, Li, Chiclana and Zeng [18] appeared to be a significant contribution to medical big data research. Similarly, Mishra, Gunasekaran, Papadopoulos and Childe [108], who investigated the applications of BDA in supply chain management, received proper citations and links. Di Vaio, Boccia, Landriani and Palladino [1] has a significant impact on AI and business models through the SDG lens. The majority of these works are from the United States or Europe.

4.7. Co-Citation Analysis

Authors can use co-citation analysis to track and examine the relationship between authors, topics, and journals [13]. Co-citation analysis was done to understand the intellectual structure of the research domain. The research domain is classified into clusters with the help of centrality index computation. It is a powerful technique to identify major themes emerging from the extant literature on a research topic [108]. When used on authors, co-citation analysis reveals the social structure of the group, whereas when used on documents, it reveals the research's intellectual structure. Articles in the same cluster share a similar area of interest and work. We performed co-citation analysis with the help of journal sources that published the articles.

As illustrated in Figure 14, we identify five distinct clusters of journal sources. Four of them each had more than ten nodes of journal sources. We decided to use journals with at least 50 citations for each source in the co-citation analysis. Only 58 articles from such sources were suitable for analysis. The first five key clusters are related to papers published in the fields of Business, Management, and Finance, as well as other social sciences. Cluster 1 is made up of 14 distinct nodes that were published in 13 different Q1 or Q2 journals. Similarly, Cluster 2 contained 13 nodes containing articles published in 11 different journals about the engineering, building, and construction industries' respective safety practises. Cluster 3 contains a total of 16 articles from the fields of Healthcare, Medicine, and Public Health. Ten of the 58 articles were about Industry 4.0 and big data applications, and artificial intelligence in sustainable supply chain management. The last four pieces, the smallest of the five, discussed various aspects of AI and BDA applications in the hospitality, tourism, and travel sectors.

4.8. Content Analysis of Thematic Areas

Table 7 show five clusters generated from the co-citation analysis by journal source publishing on AI & its sub-sets and BDA. In this section, we analyse the content of such top highly cited 58 articles published across different disciplines.

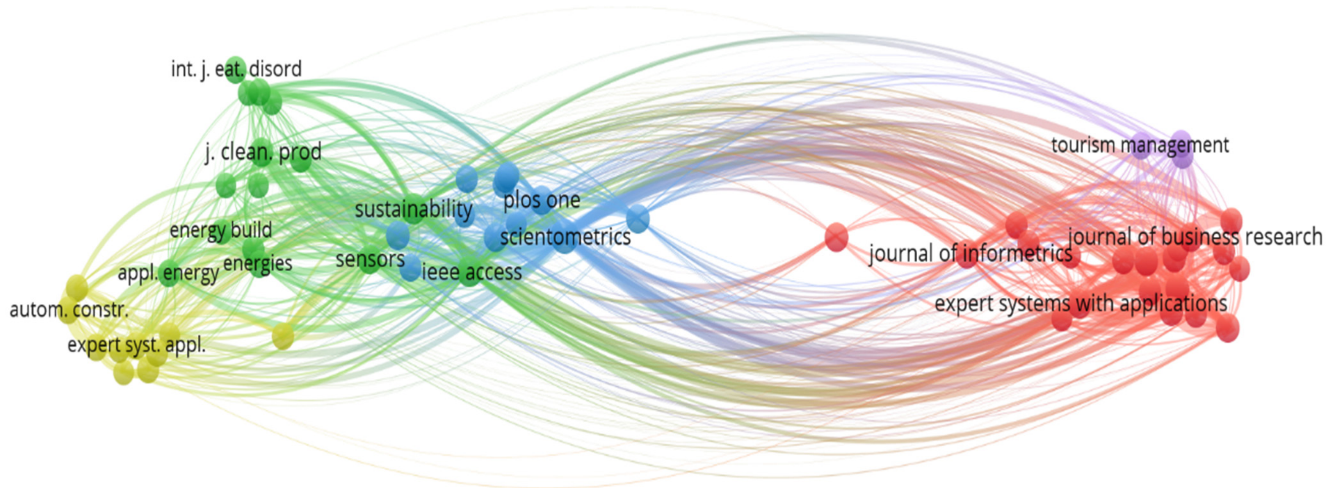

Figure 14. Co-citation analysis network of Journal Sources. **Note:** Minimum Publication = 1; minimum Citations = 50.

Table 7. Top Bibliometric Articles by Citations in Scopus.

Authors	Title	Year	Source Title	TC	TC/Y
***Cluster 1:* Business, Management, & Finance**					
Chen, Chiang and Storey [4]	Business intelligence and analytics: From big data to big impact	2012	*MIS Quarterly: Management Information Systems*	3378	307
Di Vaio, Palladino, Hassan and Escobar [5]	Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review	2020	*Journal of Business Research*	141	47
López-Robles, Otegi-Olaso, Gómez and Cobo [2]	30 years of intelligence models in management and business: A bibliometric review	2019	*International Journal of Information Management*	130	32.5
Rialti, Marzi, Ciappei and Busso [82]	Big data and dynamic capabilities: a bibliometric analysis and systematic literature review	2019	*Management Decision*	77	19.25
Khanra, Dhir and Mäntymäki [13]	Big data analytics and enterprises: a bibliometric synthesis of the literature	2020	*Enterprise Information Systems*	76	25.33
Ardito, Scuotto, Del Giudice and Petruzzelli [11]	A bibliometric analysis of research on Big Data analytics for business and management	2019	*Management Decision*	70	17.5
Wamba and Mishra [111]	Big data integration with business processes: a literature review	2017	*Business Process Management Journal*	68	11.33
Batistič and van der Laken [12]	History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations	2019	*British Journal of Management*	66	16.5
Hinojo-Lucena, et al. [112]	Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature	2019	*Education Sciences*	59	14.75
Zhang, et al. [113]	Detecting and predicting the topic change of Knowledge-based Systems: A topic-based bibliometric analysis from 1991 to 2016	2017	*Knowledge-Based Systems*	58	9.7
Bresciani, et al. [114]	Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda	2021	*International Journal of Information Management*	44	22
Wamba, Bawack, Guthrie, Queiroz and Carillo [14]	Are we preparing for a good AI society? A bibliometric review and research agenda	2021	*Technological Forecasting and Social Change*	41	20.5

Table 7. *Cont.*

Authors	Title	Year	Source Title	TC	TC/Y
Gupta and Rani [77]	A study of big data evolution and research challenges	2019	*Journal of Information Science*	35	8.75
Goodell, Kumar, Lim and Pattnaik [34]	Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis	2021	*Journal of Behavioral and Experimental Finance*	32	16
Cluster 2: Engineering & Construction Safety					
Yin, et al. [115]	Building information modelling for off-site construction: Review and future directions	2019	*Automation in Construction*	141	35.25
Jin, Zou, Piroozfar, Wood, Yang, Yan and Han [109]	A science mapping approach-based review of construction safety research	2019	*Safety Science*	106	26.5
Kaffash, et al. [116]	Big data algorithms and applications in intelligent transportation system: A review and bibliometric analysis	2021	*International Journal of Production Economics*	73	36.5
Hashem, Chang, Anuar, Adewole, Yaqoob, Gani, Ahmed and Chiroma [81]	MapReduce: Review and open challenges	2016	*Scientometrics*	58	8.29
Niu, et al. [117]	Global research on artificial intelligence from 1990–2014: Spatially-explicit bibliometric analysis	2016	*ISPRS International Journal of Geo-Information*	56	8
Sun, Wang, Wang, Li, Li and Fu [69]	Research Progress on Few-Shot Learning for Remote Sensing Image Interpretation	2021	*IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*	56	28
Shukla, Janmaijaya, Abraham and Muhuri [31]	Engineering applications of artificial intelligence: A bibliometric analysis of 30 years (1988–2018)	2019	*Engineering Applications of Artificial Intelligence*	54	13.5
Yu, Xu and Wang [66]	Bibliometric analysis of support vector machines research trend: a case study in China	2020	*International Journal of Machine Learning and Cybernetics*	53	17.67
Lin, Shen, Zhou and Xu [65]	Risk assessment and management of excavation system based on fuzzy set theory and machine learning methods	2021	*Automation in Construction*	52	26
Forcael, et al. [118]	Construction 4.0: A literature review	2020	*Sustainability (Switzerland)*	49	16.33
Montoya, García-Cruz, Montoya and Manzano-Agugliaro [32]	Power quality techniques research worldwide: A review	2016	*Renewable and Sustainable Energy Reviews*	48	6.9
Munawar, et al. [119]	Big data and its applications in smart real estate and the disaster management life cycle: A systematic analysis	2020	*Big Data and Cognitive Computing*	44	14.67
Osarogiagbon, et al. [120]	Review and analysis of supervised machine learning algorithms for hazardous events in drilling operations	2021	*Process Safety and Environmental Protection*	34	17
Cluster 3: Healthcare					
Faust, Hagiwara, Hong, Lih and Acharya [68]	Deep learning for healthcare applications based on physiological signals: A review	2018	*Computer Methods and Programs in Biomedicine*	528	106
Liao, Tang, Luo, Li, Chiclana and Zeng [18]	A bibliometric analysis and visualization of medical big data research	2018	*Sustainability (Switzerland)*	252	50.4
Tran, et al. [121]	Global evolution of research in artificial intelligence in health and medicine: A bibliometric study	2019	*Journal of Clinical Medicine*	120	30

Table 7. *Cont.*

Authors	Title	Year	Source Title	TC	TC/Y
Zhao, et al. [122]	Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse	2020	*Process Safety and Environmental Protection*	107	35.67
Khudzari, et al. [123]	Bibliometric analysis of global research trends on microbial fuel cells using Scopus database	2018	*Biochemical Engineering Journal*	104	20.8
Gu, Li, Li and Liang [94]	Visualizing the knowledge structure and evolution of big data research in healthcare informatics	2017	*International Journal of Medical Informatics*	97	16.17
Quer, et al. [124]	Machine Learning and the Future of Cardiovascular Care: JACC State-of-the-Art Review	2021	*Journal of the American College of Cardiology*	74	37
Guo, Hao, Zhao, Gong and Yang [27]	Artificial intelligence in healthcare: Bibliometric analysis	2020	*Journal of Medical Internet Research*	69	23
Chen, Xie, Wang, Liu, Xu and Hao [72]	A bibliometric analysis of natural language processing in medical research	2018	*BMC Medical Informatics and Decision Making*	69	13.8
Rahimi, Chen and Gandomi [28]	A review on COVID-19 forecasting models	2021	*Neural Computing and Applications*	63	31.5
Takahashi and Kajikawa [125]	Computer-aided diagnosis: A survey with bibliometric analysis	2017	*International Journal of Medical Informatics*	49	8.17
Goeldner, Herstatt and Tietze [75]	The emergence of care robotics—A patent and publication analysis	2015	*Technological Forecasting and Social Change*	47	5.88
dos Santos, Steiner, Fenerich and Lima [93]	Data mining and machine learning techniques applied to public health problems: A bibliometric analysis from 2009 to 2018	2019	*Computers and Industrial Engineering*	46	11.5
Gu, et al. [126]	Visualizing the intellectual structure and evolution of electronic health and telemedicine research	2019	*International Journal of Medical Informatics*	35	8.75
Tran, McIntyre, Latkin, Phan, Vu, Nguyen, Gwee, Ho and Ho [121]	The current research landscape on the artificial intelligence application in the management of depressive disorders: A bibliometric analysis	2019	*International Journal of Environmental Research and Public Health*	35	8.75
Bao, et al. [127]	Soft robotics: Academic insights and perspectives through bibliometric analysis	2018	*Soft Robotics*	92	18.4
Cluster 4: Industry 4.0 & Sustainable Operations					
Muhuri, et al. [128]	Industry 4.0: A bibliometric analysis and detailed overview	2019	*Engineering Applications of Artificial Intelligence*	237	59.25
Dhamija and Bag [46]	Role of artificial intelligence in operations environment: a review and bibliometric analysis	2019	*TQM Journal*	62	20.667
Mishra, Gunasekaran, Papadopoulos and Childe [108]	Big Data and supply chain management: a review and bibliometric analysis	2018	*Annals of Operations Research*	146	29.2
Nobre and Tavares [129]	Scientific literature analysis on big data and internet of things applications on circular economy: a bibliometric study	2017	*Scientometrics*	195	32.5
Tseng, et al. [130]	Sustainable industrial and operation engineering trends and challenges Toward Industry 4.0: a data driven analysis	2021	*Journal of Industrial and Production Engineering*	100	50
Kipper, et al. [131]	Scopus scientific mapping production in industry 4.0 (2011–2018): a bibliometric analysis	2020	*International Journal of Production Research*	82	27.33
Manesh, Pellegrini, Marzi and Dabic [110]	Knowledge Management in the Fourth Industrial Revolution: Mapping the Literature and Scoping Future Avenues	2021	*IEEE Transactions on Engineering Management*	78	39

Table 7. *Cont.*

Authors	Title	Year	Source Title	TC	TC/Y
Ding, Jin, Li and Feng [36]	Smart logistics based on the internet of things technology: an overview	2021	*International Journal of Logistics Research and Applications*	68	34
Rialti, Marzi, Ciappei and Busso [82]	Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions	2021	*Expert Systems with Applications*	33	16.5
Munim, et al. [132]	Big data and artificial intelligence in the maritime industry: a bibliometric review and future research directions	2020	*Maritime Policy and Management*	66	22
Cluster 5: Tourism & Hospitality Studies					
Mäntylä, Graziotin and Kuutila [73]	The evolution of sentiment analysis—A review of research topics, venues, and top cited papers	2018	*Computer Science Review*	284	57
Nusair [133]	A bibliometric analysis of social media in hospitality and tourism research	2019	*International Journal of Contemporary Hospitality Management*	44	11
Nusair, et al. [134]	Developing a comprehensive life cycle framework for social media research in hospitality and tourism: A bibliometric method 2002–2018	2020	*International Journal of Contemporary Hospitality Management*	43	14.33
Liu, et al. [135]	Hot topics and emerging trends in tourism forecasting research: A Scientometrics review	2019	*Tourism Economics*	35	8.75

Cluster 1: AI & BDA in Business, Management, & Finance

Chen, Chiang and Storey [4] argue that Business intelligence and analytics (BI&A) has emerged as an important area of research for both practitioners and academics, reflecting the magnitude and impact of data-related problems to be solved in modern business organizations. They discovered that data, analytics, impacts, and supporting technologies would be crucial business intelligence drivers. López-Robles, Otegi-Olaso, Gómez and Cobo [2] summarise the models of "intelligence" in management and business. They argue that: (a) intelligence is recognized as an emerging discipline in the era of big data; (b) it would have a significant impact on the innovation performance of an organization; (c) its activities are geared toward both tactical and strategic decision making; (d) it aims to improve enterprise competitiveness and economic sectors and (e) it is an ethical and legal practice.

Wamba, Bawack, Guthrie, Queiroz and Carillo [14] point out that AI could disrupt every aspect of society in the 21st century. Preparing for a "good AI society" has become a hot topic, with a growing public and scientific interest in the principles, policies, incentives, and ethical frameworks needed for society to benefit from AI while minimizing its risks. They propose 136 evidence-based research questions to understand AI-induced social changes and prepare for a "good AI society". Di Vaio, Palladino, Hassan and Escobar [5] provide a comprehensive bibliometric review of AI and business models from the perspective of the SDGs. They specifically examined the role of AI in developing sustainable business models (SBMs), which attain SDG #12 of the United Nations outlined in the UN 2030 agenda. Verma, Sharma, Deb and Maitra [35] review research on AI in marketing. They show how AI can be used in marketing strategy and plan formulations, product management, pricing management, place management, and promotion management. It brings out studies relating to Autonomous CEM, AI-driven enhanced customer experience through chatbots, ML algorithm-based marketing data processing, analysing customer habits and purchase patterns, AI-enabled machines to track five human senses to improve e-commerce businesses, and world-class SCM smart retail stores.

Batistič and van der Laken [12] illustrate how BDA can enhance organizational performance. In addition, they identify several research fields undergoing rapid growth, including financial and customer risk management, text mining, and evolutionary algorithms. This BDA would aid in organizational performance. Rialti, Marzi, Ciappei and Busso [82] summarise four major clusters of dynamic capabilities and big data: decision-making, knowledge management, supply chain management, BDA and business process management. Bresciani, Ciampi, Meli and Ferraris [114] display how big data can be used to improve co-innovation processes. They argue that open innovation, co-creation and collaborative innovation should be merged to understand data-driven innovation. BDA allows for the development of passive and unintentional co-innovation processes. Khanra, Dhir and Mäntymäki [13] evaluate the opportunities and challenges of BDA in enterprises. Their content and thematic analysis found that BDA is a significant input for strategic decision-making. The article also notes that BDA adoption is picking up pace as the cost of data acquisition decreases. Moreover, BDA has extensively been used in efficient supply chain management.

Goodell, Kumar, Lim and Pattnaik [34] also carried out a similar bibliometric review. They also find similar terms such as optimization algorithm for financial distress and corporate failure modelling, Algo-trading or high-frequency trading, text mining & sentiment analysis, financial fraud detection, convolution algorithm for pricing and valuation of derivatives, and Investor behavior prediction and trade classification using TORQ Data. Prado, et al. [136] show how neural networks became significant in predicting corporate bankruptcy and credit risk to improve bank lending and profitability. By applying bibliometric analysis, Ahmed, Alshater, El Ammari and Hammami [103] unearth that AI and ML are now applied in different areas of finance. Their review highlighted an increasing trend in AI and ML applications. It has been applied to bankruptcy prediction, stock price prediction, portfolio management, oil price prediction, anti-money laundering, behavioural finance, BDA, and Blockchain. Typically, such findings provide market participants, especially fintech and finance firms, with guidance on how AI and ML can be applied to their decision-making.

Hinojo-Lucena, Aznar-Díaz, Cáceres-Reche and Romero-Rodríguez [112] examined the applications of AI in Education and their impact on scientific literature. They concluded that despite the existence of AI, the body of knowledge about its use in higher education is still fragmented. Erevelles, Fukawa and Swayne [40] identified the pattern in the topic change of knowledge-based systems (KnoSys). A Latent Dirichlet Allocation (LDA) topic modelling is used to profile the hotspots of KnoSys and predict possible future trends from a probabilistic perspective. They identified six primary research areas of KnoSys, i.e., expert systems, ML, data mining, decision making, optimization, and fuzzy, and the results also indicate that the interest of KnoSys communities in the area of computational intelligence is raised, and the ability to construct practical systems through knowledge use and accurate prediction models is highly emphasized.

Cluster 2: AI and BDA in Engineering and Construction Safety

Engineering and computer science journals also published insightful bibliometric articles on various sub-fields. Shukla, Janmaijaya, Abraham and Muhuri [31] summarized the engineering applications of AI for over 30 years. They showed that AI research and its extensive engineering applications began in 2012-13 years onwards. The research contributions have also been exponentially growing over the past decade. Some of the influential contributions they identified were on time-series data mining, ANN and SVM for bearing fault detection, hybrid neural network and ARIMA model for time-series water quality predictions, Auto ID systems, intelligent manufacturing controls, particle swarm optimization, genetic algorithms, fuzzy logic, and so forth.

Lin, Shen, Zhou and Xu [65] reviewed articles and showed how fuzzy set theory and ML methods could be applied to assess the risks and manage excavation construction. They also illustrate how the random forest model can be applied to evaluate the excavation system's risk. Forcael, Ferrari, Opazo-Vega and Pulido-Arcas [118] review the Construction 4.0 sub-concept introduced in Germany in 2016. They argue that the construction digitalization of the construction process constitutes Construction 4.0. They emphasized the applications of BDA, robotics in production, mobile logistics, drones, autonomous vehicles, IoT, cybersecurity, BIM, Augmented Reality, Virtual Reality, laser Scanners, Blockchain, Wearable sensors, and construction equipment with sensors are all activating the construction 4.0. Sun, Wang, Wang, Li, Li and Fu [69] studied deep learning solutions to interpret remote sensing images. They reviewed investigations about few-shot learning for remote sensing picture interpretation. They highlight data-augmentation-based and prior-knowledge-based approaches of few-shot learning for interpretation. Three typical remote sensing interpretation applications are presented, including scene categorization, semantic segmentation, and object detection, along with their accompanying public datasets and assessment criteria.

Munawar, Qayyum, Ullah and Sepasgozar [119] illustrate that big data's applications in smart real estate and disaster management life cycle. They emphasized that Hadoop and Apache Spark are big data management frameworks that must capture the data's holistic essence and make analyses meaningful, fast, and efficient. Similarly, Hashem, Chang, Anuar, Adewole, Yaqoob, Gani, Ahmed and Chiroma [81] show the tools of big data, MapReduce and Hadoop Distributed File System (HDFS), and its sub-tool MapReduce is used for distributed and scalable processing of big data. MapReduce computational paradigm is a significant enabler for underlying numerous big data platforms. Another important emergent area in the engineering field is Building Information Modelling (BIM) for off-site construction (OSC) [115]. Yin, Liu, Chen and Al-Hussein [115] also found the reviews of BIM-enabled BDA for the best off-site construction cloud-based data exchange for OSC, robotics and 3D printing for OSC, and so forth. The same synthesized the current state of BIM for OSC and identified the research needs to advance in the practice of Architecture, Engineering and construction. Similar to this, Jin, Zou, Piroozfar, Wood, Yang, Yan and Han [109] conducted a review on BIM in safety management. The proposed future direction for an adaptable safety climate and safety culture model; prototypes, continuous development, and readiness to apply information technologies in safety management. They also identified subgroups factors linked to cognitive models of workers' safety perceptions and behaviours; and artificial intelligence and smart technologies in safety program management.

Montoya, García-Cruz, Montoya and Manzano-Agugliaro [32] reread the subject of power quality published between 1970 through 2013. An analysis of techniques such as heuristic optimization, AI and signal processing was also conducted within the framework of power quality. The keywords *harmonics, active filter, voltage sag, distributed generation and wavelet transform* were verified as the most commonly used terms other than power quality. *Genetic Algorithms* and *Particle Swarm Optimisation*, *Neural Network* and *Fuzzy Logic*, *Wavelet Transform* and *Fourier Analysis*, and AI and Signal Processing were the most active categories. Osarogiagbon, Khan, Venkatesan and Gillard [120] contributed an influential bibliometric review of supervised ML algorithms for hazardous events in drilling operations due to drilling fluid density/mud weight. Deep learning, random forest, and SVM applications have gained momentum.

Cluster 3: AI and BDA in Healthcare & Public Health

Cluster 3 is a pool of academic sources published predominantly in Medicare and Public Health-related subjects. Tran, McIntyre, Latkin, Phan, Vu, Nguyen, Gwee, Ho and Ho [121] note that the research on the application of AI in medicine field exponentially grew during the past decade. They show that robotic surgery, machine learning, ANN, NLP, MRI, SVM algorithm, deep learning etc., are increasingly used in the medical literature. Faust, Hagiwara, Hong, Lih and Acharya [68] reviewed 54 articles on deep learning applications based on the physiological signals in healthcare and garnered those 528 citations through our study period, making it the most influential bibliometric article published in a high-quality Scopus-indexed journal. This review article receives 105.60 citations per year. Guo, Hao, Zhao, Gong and Yang [27] summarized the applications of AI in healthcare. They found that cancer, depression, Alzheimer's disease, heart failure, and diabetes are significant health issues studied in AI research. The greatest impact on health care has been made by Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN). It also notes that the research hotspots of nucleosides, CNN, and tumour markers remained. Khudzari, Kurian, Tartakovsky and Raghavan [123] reviewed the global research trend on the increased applications of neural networks in biomedical research on Microbial Fuel Cells (MFC). Using PATSTAT patent analysis and ISI WoS publications, Goeldner, Herstatt and Tietze [75] also found an increasing trend and emergence in the care-robotics [Care robots are a way to assist older adults with physical or mental disabilities to remain as autonomous as possible or regain autonomy that has been lost (e.g., running stairs). Quer, Arnaout, Henne and Arnaout [124] conducted an open-source bibliometric analysis of ML application in Cardiological treatment. They articulate that ML algorithms are capable of identifying complex patterns in medical data and have the potential to enhance cardiovascular care.

BDA in health care means analysing large datasets from thousands of patients, identification of clusters and correlations between datasets, and developing predictive models using data mining techniques [18]. Liao, Tang, Luo, Li, Chiclana and Zeng [18] also reviewed Medical Big Data (MBD) and found an increasing trend over the past years. In addition, there has been an increase in research interest in MBD among medical researchers, with 50 citations per year after publication. Chen, Xie, Wang, Liu, Xu and Hao [72] contributed a review on the applications of NLP in medical research. They noticed that NLP-empowered medical research publications are in increasing trend. They found 1405 NLP-enhanced medical research publications between 2008 through 2018, with an average annual growth rate of 18.39%. Computational biology, terminology mining, information extraction, text classification, social media as a source of data, information retrieval, and other major thematic areas were among the ten areas that were identified. Another Influential study by Gu, Li, Li and Liang [94] also contributed a summary of research articles on the applications of big data research in healthcare informatics. Gu, Li, Wang, Yang and Yu [126] show how electronic health (e-health) records, mobile health care, smart health and telemedicine research evolved over time. It appears that Medical and Healthcare Journals have already begun investigating the use of AI and BDA. Takahashi and Kajikawa [125] discover that computer-aided diagnosis (CAD) assists clinical decision support systems. CAD mammograms eventually advanced to include brain diseases. They show that test datasets must be normalized, and an evaluation method is necessary to implement a data-driven algorithm or a system for CAD.

dos Santos, Steiner, Fenerich and Lima [93] reviewed the data mining and ML technique applied to public health problems. They found that SVM was the most common ML algorithm applied to research public health problems. Tran, McIntyre, Latkin, Phan, Vu, Nguyen, Gwee, Ho and Ho [121] show how AI and ML can be applied to diagnose and treat depressive disorders and find emerging themes such as diagnosis accuracy, structural imaging techniques, gene testing, drug development, pattern recognition, and electroencephalography (EEG)-based diagnosis. Rahimi, Chen and Gandomi [28] reviewed different COVID-19 epidemic forecasting models proposed. They show that deep learning methods such as Long Short-term memory (LSTM) networks, neural networks, along with polynomial neural networks (nature-inspired algorithm) are suggestive of predicting susceptible, infected, recovered, and deceased (SIRD) models. Similarly, the Phenomenological model also uses an adaptive neuro-fuzzy inference system, regression tree algorithm, SVM, etc., to predict the pandemic. Zhao, Dai, Qiao, Sun, Hao and Yang [122] brought out new research frontiers of AI in public utility by using AI-driven wastewater treatment plants that simultaneously address pollutant removal, cost reduction, water reuse, and management challenges in complex practical applications. Bao, Fang, Chen, Wan, Xu, Yang and Zhang [127] displays that studies on soft robotics in developed countries have been increasing steadily. They identified emerging themes such as Smart materials, bionics, morphological computation, and embodiment control that are expected to contribute to this field.

Cluster 4: Industry 4.0 & Sustainable Operations

Muhuri, Shukla and Abraham [128] contributed an impactful review relating to industry 4.0 and digital integration and intelligent engineering that has taken a giant leap towards futuristic technology. Kipper, Furstenau, Hoppe, Frozza and Iepsen [131] presented 31 clusters in which the most representative motor themes were Cyber-Physical Systems, IoT, and Big Data. Moreover, it was possible to identify fields with a high investment of efforts by the scientific community, such as the union between lean production and I4.0, production-centred CPS (CPPS), IoT (Industrial Internet of Things—IIoT), among others. Tseng, Tran, Ha, Bui and Lim [130] highlighted the articles about sustainable industrial and operation engineering trends and challenges toward I4.0. They identified eight different study groups. Those groups included: lean manufacturing in I4.0; cyber-physical production system; Big data-driven and intelligent communications; safety and security; AI for sustainability; the circular economy in a digital environment; Business Intelligence and Virtual Reality, and Environmental Sustainability. Ding, Jin, Li and Feng [36] demonstrate the role and impact of IoT on smart logistics, reveal challenges of IoT-based smart logistics, and provide research needs for developing smart logistics. They identified challenges that include technical problems of radio frequency identification and wireless sensor networks, limited extension and technical capacity of IoT standardization issues of IoT, data acquisition and processing issues of IoT, and security and privacy concerns on IoT. There is a strong research need to address the key technical issues of IoT, promote various IoT technologies in logistics practice, and jointly develop advanced ICTs and management systems. Kaffash, Nguyen and Zhu [116] comprehensively reviewed 586 articles examining the most relevant big data algorithms used in Intelligent Transport Systems (ITS). They also recognize how big data algorithms to various intelligent transportation systems that integrate and adopt ITS models.

Mishra, Gunasekaran, Papadopoulos and Childe [108] conducted a detailed review of BDA in supply chain management. They unearthed six current clusters out of 286 articles on BDA in supply chain management published between 2006–2016. They identified clusters such as BDA, big data tools and algorithms, big data applications in healthcare, big data and forecasting, and data mining and applications. Dhamija and Bag [46] put forth that "AI" is the key to achieving persuasive operational transformations in most current organizational set-ups. Their bibliometric analysis emerged with clusters of AI and optimization; industrial engineering/research and automation; operational performance and ML; sustainable supply chains and sustainable development, technology adoption and green supply chain management; IoT and Reverse Logistics. Ding, Jin, Li and Feng [36] show how an intelligent logistics environment is created using new IoT technology. It calls for solid research to address IoT's technical issues and promote IoT-enabled smart logistics practices. Such practice would help develop advanced ICT and management systems. [100] show that there is considerable research enquiring about the applications of AI and BDA in the maritime industry. They identified four major clusters of the research area: (1) digital transformation in the maritime industry, (2) applications of big data from Automatic Identification Systems (AIS), (3) energy efficiency, and (4) predictive analytics. Riahi, et al. [137] show how AI has been applied in the supply chain management processes. They note that ML, NLP, and robotics are all potential enablers of supply chain transformation.

Nobre and Tavares [129] argued that Innovative technologies such as big data and IoT have the potential to facilitate the adoption of circular economy concepts by organizations and society, making them more pervasive in our everyday lives. They conducted a bibliometric review of the articles published in Scopus journals between 2006–2015 to explore the application of Big Data/IoT in the context of a circular economy. Out of 32,550 unique big data/IoT studies, they chose 70 matching publications that went through content and social network analysis using the R-studio statistical tool. We then compared it to some current industry initiatives. Bibliometrics findings indicate that China and USA are the most interesting countries in the area and reveal a context with significant research opportunities. Manesh, Pellegrini, Marzi and Dabic [110] necessitate an in-depth comprehension of Knowledge Management (KM) processes, specifically how knowledge is created, shared/transferred, acquired, stored/retrieved, and applied across an organization's system in I4.0–context—which involves the interconnectedness of machines and their ability to learn and share data autonomously.

Cluster 5: AI and BDA in Travel & Tourism

In a tourism research context, Nusair, Butt and Nikhashemi [134] discover six new areas within the consumer behaviour research theme: eWOM, service recovery, customer satisfaction, brand/destination image and service quality. They also note that new trends in social media and tourism-related research are big data, netnography, Travel 2.0 and Web 2.0. Again, Nusair [133] found that the period 2013–2018 has witnessed newly emerging trends such as "Big Data", "e-tourism", "green experience", and "smart tourism" in social media research in hospitality and tourism. Liu, Liu, Wang and Pan [135] identified an increasing trend in applying ANN, Support vector regression, and neural network models in the tourism forecasting model during the past decade. Mäntylä, Graziotin and Kuutila [73] shows the applications of NLP tools, sentiment analysis by text mining, topic modelling, and latent Dirichlet Allocation to understand product reviews. Such sentiment analysis has been applied in stock market buying, elections, disasters, medicine, software engineering, and Cyberbullying.

5. Key Findings from Bibliometric Techniques

In a quest to provide all-inclusive knowledge on the status of AI and BDA research investigations, this study revisited highly insightful bibliometric reviews published in the high-quality journal of different disciplines. We duly address five relevant research questions put forth. We address the first four research questions to understand how much bibliometric reviews have been carried out on AI and BDA and their author, affiliations, journal source and country source statistics. The summary of results is as follows:

1. ***Key Authors:*** As seen in Table 3 and Figure 9 (Top-ten productive authors), Figure 13 and Table 6 (Bibliometric coupling by documents), and Table 7 (Co-citation analysis by Journals) show the highly relevant authors in different fields. As per Table 3, our study shows that most productive authors in different areas do not significantly impact their respective fields. However, the presence of BDA and Business Intelligence [68]; Deep Learning in Health Care [5]; AI-driven business model for sustainable development [18]; Medical Big Data research [108]; BDA in the supply chain [13]; BDA in Enterprise [82]; dynamic capabilities of big data [11]; BDA in business management [111]; BDA in business process management were essentially creating impact in different fields, according to our criteria.
2. **Key Organizations:** As shown in Figure 7, Regarding the influential affiliations, our findings indicate that Symbiosis International Deemed University, Pune (India) has been conducting bibliometric reviews in various subject areas as per Scopus Analyser. Chinese Academy of Science also contributed a significant number of documents, followed by Malaviya National Institute of Technology, Jaipur (India) contributed a good number of documents over the past ten years. The University of Technology, Sydney (Australia) and the University of Grenada (Spain) also have made exemplary contributions.
3. ***Key Countries and Collaboration:*** Five countries, the USA, the UK, China, India, and Malaysia, have a good role in contributing the bibliometric review articles to these two research areas. Likewise, the collaboration among these five countries is vital and has offered good research outcomes.
4. ***Key Journals:*** By Tables 4 and 7, and Figure 10, AI and BDA bibliometric research have a substantial impact on fields including Computer Science, Engineering, Business, Management, and Finance. The important journals are (1) Business and Operations: *Journal of Business Research; Technological Forecasting and Social Change; Annals of Opera-*

tions Research, *MIS Quarterly: Management Information Systems; Management Decision*, *Sustainability (Switzerland), International Journal of Information Management*, etc. (2) Computer Science & Engineering: *Expert Systems with Applications*; *Scientometrics, Computer Science Review*, *Engineering Applications of Artificial Intelligence*; *IEEE Access, Automation in Construction;* and (3) Medicine & Healthcare: *International journal of medical informatics, Journal of Medical Internet Research*, *Computer Methods and Programs in Biomedicine.* There is much scope for bibliometric reviews of AI and BDA in Arts & Humanities, Economics and Finance, and Energy and Environmental Science.

5. ***Key Studies:*** Over the past decade, from 2012 through 2022, we have identified the most prestigious studies examining the applications in AI & its sub-sets and BDA in Business and Management, Engineering and Construction Safety, Medicare, I4.0, Sustainable Operations and Supply Chain, and Tourism studies (Table 7). The individual results imply that the first set of articles focused on reviewing conceptualizing the business value of "Intelligence" or "Artificial Intelligence" and "Big Data Analytics" in Business and Management [4,14], AI-driven business models in SDGs era [5] and the use of BDA in enterprises [13] in a general sense. Cluster 2 of Table 7 shows significant reviews carried out in Engineering and Construction safety. Engineering applications of AI over the past 30 years by Shukla, Janmaijaya, Abraham and Muhuri [31] is a one-stop review to comprehend the trend of AI in engineering. Another set of studies enquiring about the fuzzy set theory application for excavation construction management [65]; construction 4.0 [118]; deep learning application to interpret the remote sensing images [69]; big data applications in smart real-estate and disaster management and BIM-enabled BDA for off-site construction [64].

Cluster 3 of journals shows key bibliometric reviews of AI and BDA in Medicare. Faust, Hagiwara, Hong, Lih and Acharya [68] remain the influential reviews on applications of deep learning to carry out medical diagnosis and treatment using physiological signals. Some articles, such as the summary of AI in healthcare by [126], the neural network in biomedical research [123], care robotics [75]. Similarly, BDA and its applications are also well-reviewed in the medical literature. Studies such as medical big data research [18]; NLP in medical research [72]; BDA for healthcare informatics [94]; ML applications in addressing public health problems [93]; AI and ML applications to treat depressive disorders; AI for water-waste management [122] are some of the impactful studies that summarized applications of AI and BDA in Healthcare and public health.

The fourth cluster of highly prestigious bibliometric reviews, in turn, shed light on the value of the Intelligent Transport system model in supply chain management [116]; sustainable industrial operations [130]; Industry 4.0 [128]; enterprise operational transformation [46]; smart logistics in IoT environment [36]; BDA in the circular economy [129]. The final cluster lists some of the key studies in the tourism industry by Nusair [133], Nusair, Butt and Nikhashemi [134], and Liu, Liu, Wang and Pan [135]. However, articles published in the last few years are yet to gain enough traction to be included in Table 7.

5.1. Future Research Directions

Based on fourth and fifth questions aimed to identify potential future research avenues from the extant bibliometric literature. Findings from this study put forward several future research directions in connection with the AI and BDA research carried out in five identified clusters (See Table 7). The future research directions are proposed for the following streams of inquiry:

(a) *Specialization in AI sub-domains and BDA tools:* AI is a wholistic technology-driven tool that currently has six sub-domains: Machine Learning [66]; Deep Learning [68]; NLP [72]; Robotics [75]; Fuzzy Logic [65]; and Expert Systems [14]. Future researchers can pay individual attention to each sub-domains and explore its applications in various domain knowledge. Likewise, BDA is a holistic approach to managing, processing, and analysing big data [13]. Thus, BDA arch over a diverse set of tools, such as data mining, multimedia analytics [138], and cognitive modelling [139]. Future research may be dedicated to grasping the worth offered by a specific BDA tool to management, business, government and policymaking.

(b) *AI and BDA in Select Management Domains*: A variety of management-related fields are investigating AI and BDA applications, including Agriculture [37], Education [27,112], Health [52], Business models [111], Intelligent manufacturing [130], Marketing retail [35], Travel and tourism [133]; and Supply chains [108]. Nevertheless, research summarizing the use cases of AI and BDA technologies in fields such as corporate governance, tax, auditing and accounting, and sports administration is limited.

(c) *Contributing to Smaller Thematic Areas:* Clusters of bibliometric reviews generated from the co-citation analysis reported a trend in using AI and BDA within specific domains. For example, a thematic area's intellectual capital was established around BDA's applications in supply chain management and medical big data research. Likewise, bibliometric reviews relating to AI applications and use cases and their sub-domains in healthcare, engineering, and sustainability are abundant. Even though the literature on the use of AI and BDA in other domains, namely accounting and auditing [34], blockchain technology and cryptography [103], robotics and expert systems [127], topic modelling and NLP [73], IoT and smart logistics [36] among others appear fragmented.

(d) *Empirical Research Base:* Review articles generally contribute to establishing a research topic; then, studies using more rigorous methodologies are used. Several bibliometric articles in different fields have been done on using BDA and AI. Thus, the literature summary may greatly benefit the development of 'measurement instruments' and empirically test the benefits offered by AI and BDA to solve different real-world problems.

(e) *Legal and Ethical Concerns:* Concerns for user privacy and data security may undermine the utility of AI and BDA in various fields [139]. However, existing corporate law cannot provide justice in disputes involving such challenges [14]. Therefore, corporate governance and business law researchers may need to develop legal frameworks that sustain the value offered by AI and BDA in various domains while upholding ethical Standards.

5.2. Contribution to Theory

The study contributes to the existing literature by summarizing the "bibliometric reviews" on AI and BDA, as it is the first novel paper on a review. This exhaustive bibliometric analysis of past reviews may serve as a "one-stop-shop" for the latest literature on AI and BDA in six fields. This article would serve as a starting point for researchers interested in the applications of AI and its subsets, as well as BDA in Business and Economics, Healthcare, Engineering and Construction Safety, I4.0 and Sustainable Operations/Supply Chain Management, and Tourism. Our bibliometric summary contributes to the UN's SDG #12 goal of ensuring sustainable production and consumption patterns through innovation, technologies, and science. The study compiles and structures extant reviews and identifies five key areas of research that carried out a significant number of bibliometric reviews. The keyword co-occurrences of sustainability, circular economy, I.40, and other terms indicate that these five different fields are gradually directing their research toward sustainable development goals as well. Actionable future research directions emerging from the five identified clusters will interest researchers. Future researchers may also adopt the protocol for bibliometric studies developed in this study to provide structure to other fragmented bodies of knowledge.

5.3. Contribution to Managerial Practice

Many businesses struggle to get the intended return on investment while obtaining the necessary resources to reap the advantages of AI-driven technology and BDA. This research might aid businesses in conducting a more accurate cost-benefit analysis by giving a detailed overview of use concepts, use cases, tools, and applications of AI and its sub-sets and BDA. Frequently, the advantages of AI-driven technology and BDA come at the sacrifice of the data privacy of users. Policymakers may explore adopting legislative frameworks prohibiting businesses from using large user data and AI tools. Ethical businesses may voluntarily address the data privacy concerns of consumers. R&D teams at non-academic organizations may find this review of bibliometric studies methodologically useful in picking the proper previous literature. Overall, the bibliometric summary for five different discipline clusters would assist managers in understanding the AI and BDA application trends in their respective sectors and industries.

5.4. Limitations of the Study

Our review is based on particular keywords to analyze literature using bibliometric analysis on AI and Big Data Analytics for the last ten years, and it is possible that different keywords would have generated different results. That is, as this is a summary of bibliometric reviews in AI and BDA research in various fields, it is possible that there are numerous highly cited works on AI and BDA applications in various fields might have been omitted. We used Vosviewer and R-package for our study; other software like R–Package, Bibecel, SciMAT, Sci 2 Tool, Pakej, and Citespace may also be used.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15054026/s1, File S1. Database.

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References

1. Di Vaio, A.; Boccia, F.; Landriani, L.; Palladino, R. Artificial intelligence in the agri-food system: Rethinking sustainable business models in the COVID-19 scenario. *Sustainability* **2020**, *12*, 4851. [CrossRef]
2. López-Robles, J.R.; Otegi-Olaso, J.R.; Gómez, I.P.; Cobo, M.J. 30 years of intelligence models in management and business: A bibliometric review. *Int. J. Inf. Manag.* **2019**, *48*, 22–38. [CrossRef]
3. Sjödin, D.; Parida, V.; Palmié, M.; Wincent, J. How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *J. Bus. Res.* **2021**, *134*, 574–587. [CrossRef]
4. Chen, H.; Chiang, R.H.; Storey, V.C. Business intelligence and analytics: From big data to big impact. *MIS Q.* **2012**, *1*, 1165–1188. [CrossRef]
5. Di Vaio, A.; Palladino, R.; Hassan, R.; Escobar, O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *J. Bus. Res.* **2020**, *121*, 283–314. [CrossRef]
6. Davenport, T.H.; Ronanki, R. Artificial intelligence for the real world. *Harv. Bus. Rev.* **2018**, *96*, 108–116.
7. Davenport, T.; Guha, A.; Grewal, D.; Bressgott, T. How artificial intelligence will change the future of marketing. *J. Acad. Mark. Sci.* **2020**, *48*, 24–42. [CrossRef]
8. Colson, E. What AI-Driven Decision Making Looks Like. Harvard Business Review. 2019. Available online: https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like (accessed on 15 January 2023).
9. Lichtenthaler, U. Extremes of acceptance: Employee attitudes toward artificial intelligence. *J. Bus. Strategy* **2020**, *41*, 39–45. [CrossRef]
10. Wiener, M.; Saunders, C.; Marabelli, M. Big-data business models: A critical literature review and multiperspective research framework. *J. Inf. Technol.* **2020**, *35*, 66–91. [CrossRef]
11. Ardito, L.; Scuotto, V.; Del Giudice, M.; Petruzzelli, A.M. A bibliometric analysis of research on Big Data analytics for business and management. *Manag. Decis.* **2019**, *57*, 1993–2009. [CrossRef]

12. Batistič, S.; van der Laken, P. History, evolution and future of big data and analytics: A bibliometric analysis of its relationship to performance in organizations. *Br. J. Manag.* **2019**, *30*, 229–251. [CrossRef]
13. Khanra, S.; Dhir, A.; Mäntymäki, M. Big data analytics and enterprises: A bibliometric synthesis of the literature. *Enterp. Inf. Syst.* **2020**, *14*, 737–768. [CrossRef]
14. Wamba, S.F.; Bawack, R.E.; Guthrie, C.; Queiroz, M.M.; Carillo, K.D.A. Are we preparing for a good AI society? A bibliometric review and research agenda. *Technol. Forecast. Soc. Chang.* **2021**, *164*, 120482. [CrossRef]
15. Donthu, N.; Kumar, S.; Mukherjee, D.; Pandey, N.; Lim, W.M. How to conduct a bibliometric analysis: An overview and guidelines. *J. Bus. Res.* **2021**, *133*, 285–296. [CrossRef]
16. Hu, F.; Liu, W.; Tsai, S.-B.; Gao, J.; Bin, N.; Chen, Q. An empirical study on visualizing the intellectual structure and hotspots of big data research from a sustainable perspective. *Sustainability* **2018**, *10*, 667. [CrossRef]
17. Abdollahi, A.; Rejeb, K.; Rejeb, A.; Mostafa, M.M.; Zailani, S. Wireless Sensor Networks in Agriculture: Insights from Bibliometric Analysis. *Sustainability* **2021**, *13*, 12011. [CrossRef]
18. Liao, H.; Tang, M.; Luo, L.; Li, C.; Chiclana, F.; Zeng, X.-J. A bibliometric analysis and visualization of medical big data research. *Sustainability* **2018**, *10*, 166. [CrossRef]
19. Morato, J.; Sanchez-Cuadrado, S.; Iglesias, A.; Campillo, A.; Fernández-Panadero, C. Sustainable technologies for older adults. *Sustainability* **2021**, *13*, 8465. [CrossRef]
20. Cano, J.A.; Londoño-Pineda, A.; Castro, M.F.; Paz, H.B.; Rodas, C.; Arias, T. A Bibliometric Analysis and Systematic Review on E-Marketplaces, Open Innovation, and Sustainability. *Sustainability* **2022**, *14*, 5456. [CrossRef]
21. Giuffrida, N.; Fajardo-Calderin, J.; Masegosa, A.D.; Werner, F.; Steudter, M.; Pilla, F. Optimization and machine learning applied to last-mile logistics: A review. *Sustainability* **2022**, *14*, 5329. [CrossRef]
22. Samuel, G.; Lucivero, F.; Somavilla, L. The Environmental Sustainability of Digital Technologies: Stakeholder Practices and Perspectives. *Sustainability* **2022**, *14*, 3791. [CrossRef]
23. Loureiro, S.M.C.; Nascimento, J. Shaping a view on the influence of technologies on sustainable tourism. *Sustainability* **2021**, *13*, 12691. [CrossRef]
24. Hashem, I.A.T.; Anuar, N.B.; Gani, A.; Yaqoob, I.; Xia, F.; Khan, S.U. MapReduce: Review and open challenges. *Scientometrics* **2016**, *109*, 389–422. [CrossRef]
25. Zhu, J.; Zhuang, E.; Fu, J.; Baranowski, J.; Ford, A.; Shen, J. A framework-based approach to utility big data analytics. *IEEE Trans. Power Syst.* **2015**, *31*, 2455–2462. [CrossRef]
26. Min, H. Artificial intelligence in supply chain management: Theory and applications. *Int. J. Logist. Res. Appl.* **2010**, *13*, 13–39. [CrossRef]
27. Guo, Y.; Hao, Z.; Zhao, S.; Gong, J.; Yang, F. Artificial intelligence in health care: Bibliometric analysis. *J. Med. Internet Res.* **2020**, *22*, e18228. [CrossRef]
28. Rahimi, I.; Chen, F.; Gandomi, A.H. A review on COVID-19 forecasting models. *Neural Comput. Appl.* **2021**, *4*, 1–11. [CrossRef]
29. Bragazzi, N.L.; Dai, H.; Damiani, G.; Behzadifar, M.; Martini, M.; Wu, J. How big data and artificial intelligence can help better manage the COVID-19 pandemic. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3176. [CrossRef]
30. Carrillo-Perez, F.; Pecho, O.E.; Morales, J.C.; Paravina, R.D.; Della Bona, A.; Ghinea, R.; Pulgar, R.; Pérez, M.d.M.; Herrera, L.J. Applications of artificial intelligence in dentistry: A comprehensive review. *J. Esthet. Restor. Dent.* **2022**, *34*, 259–280. [CrossRef]
31. Shukla, A.K.; Janmaijaya, M.; Abraham, A.; Muhuri, P.K. Engineering applications of artificial intelligence: A bibliometric analysis of 30 years (1988–2018). *Eng. Appl. Artif. Intell.* **2019**, *85*, 517–532. [CrossRef]
32. Montoya, F.G.; García-Cruz, A.; Montoya, M.G.; Manzano-Agugliaro, F. Power quality techniques research worldwide: A review. *Renew. Sustain. Energy Rev.* **2016**, *54*, 846–856. [CrossRef]
33. Patel, J.; Shah, S.; Thakkar, P.; Kotecha, K. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Syst. Appl.* **2015**, *42*, 259–268. [CrossRef]
34. Goodell, J.W.; Kumar, S.; Lim, W.M.; Pattnaik, D. Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *J. Behav. Exp. Financ.* **2021**, *32*, 100577. [CrossRef]
35. Verma, S.; Sharma, R.; Deb, S.; Maitra, D. Artificial intelligence in marketing: Systematic review and future research direction. *Int. J. Inf. Manag. Data Insights* **2021**, *1*, 100002. [CrossRef]
36. Ding, Y.; Jin, M.; Li, S.; Feng, D. Smart logistics based on the internet of things technology: An overview. *Int. J. Logist. Res. Appl.* **2021**, *24*, 323–345. [CrossRef]
37. Couliably, S.; Kamsu-Foguem, B.; Kamissoko, D.; Traore, D. Deep learning for precision agriculture: A bibliometric analysis. *Intell. Syst. Appl.* **2022**, *15*, 200102. [CrossRef]
38. Iaksch, J.; Fernandes, E.; Borsato, M. Digitalization and Big data in smart farming—A review. *J. Manag. Anal.* **2021**, *8*, 333–349. [CrossRef]
39. Mehmood, M.U.; Chun, D.; Han, H.; Jeon, G.; Chen, K. A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. *Energy Build.* **2019**, *202*, 109383. [CrossRef]
40. Erevelles, S.; Fukawa, N.; Swayne, L. Big Data consumer analytics and the transformation of marketing. *J. Bus. Res.* **2016**, *69*, 897–904. [CrossRef]
41. Gibson, I.; Rosen, D.; Stucker, B.; Khorasani, M. Direct Digital Manufacturing. In *Additive Manufacturing Technologies*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 525–554.

42. Hoy, M.B. Alexa, Siri, Cortana, and more: An introduction to voice assistants. *Med. Ref. Serv. Q.* **2018**, *37*, 81–88. [CrossRef]
43. Chen, H.-M.; Schütz, R.; Kazman, R.; Matthes, F. How Lufthansa Capitalized on Big Data for Business Model Renovation. *MIS Q. Exec.* **2017**, *16*.
44. In, S.Y.; Rook, D.; Monk, A. Integrating alternative data (also known as ESG data) in investment decision making. *Glob. Econ. Rev.* **2019**, *48*, 237–260. [CrossRef]
45. Issa, H.; Sun, T.; Vasarhelyi, M.A. Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *J. Emerg. Technol. Account.* **2016**, *13*, 1–20. [CrossRef]
46. Dhamija, P.; Bag, S. Role of artificial intelligence in operations environment: A review and bibliometric analysis. *TQM J.* **2020**, *32*, 869–896. [CrossRef]
47. Mc Carthy, J.; Hayes, P.J. Some Philosophical Problems from The Standpoint of Artificial Intelligence. In *Readings in Artificial Intelligence*; Elsevier: Amsterdam, The Netherlands, 1981; pp. 431–450.
48. Hamet, P.; Tremblay, J. Artificial intelligence in medicine. *Metabolism* **2017**, *69*, S36–S40. [CrossRef]
49. Duan, L.; Xiong, Y. Big data analytics and business analytics. *J. Manag. Anal.* **2015**, *2*, 1–21. [CrossRef]
50. Haenlein, M.; Kaplan, A. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *Calif. Manag. Rev.* **2019**, *61*, 5–14. [CrossRef]
51. DeCanio, S.J. Robots and humans–complements or substitutes? *J. Macroecon.* **2016**, *49*, 280–291. [CrossRef]
52. Hengstler, M.; Enkel, E.; Duelli, S. Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technol. Forecast. Soc. Chang.* **2016**, *105*, 105–120. [CrossRef]
53. Kolbjørnsrud, V.; Amico, R.; Thomas, R.J. Partnering with AI: How organizations can win over skeptical managers. *Strategy Leadersh.* **2017**, 16. [CrossRef]
54. Kaplan, A.; Haenlein, M. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. [CrossRef]
55. Goertzel, B.; Pennachin, C. *Artificial General Intelligence*; Springer: Berlin/Heidelberg, Germany, 2007; Volume 2.
56. Bostrom, N. *Superintelligence: Paths, Dangers, Strategies*; Oxford University Press: London, UK, 2015.
57. Huang, F.; Vasarhelyi, M.A. Applying robotic process automation (RPA) in auditing: A framework. *Int. J. Account. Inf. Syst.* **2019**, *35*, 100433. [CrossRef]
58. Ahmed, E.; Yaqoob, I.; Hashem, I.A.T.; Khan, I.; Ahmed, A.I.A.; Imran, M.; Vasilakos, A.V. The role of big data analytics in Internet of Things. *Comput. Netw.* **2017**, *129*, 459–471. [CrossRef]
59. Goertzel, T. The path to more general artificial intelligence. *J. Exp. Theor. Artif. Intell.* **2014**, *26*, 343–354. [CrossRef]
60. Meyer-Waarden, L.; Cloarec, J. "Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. *Technovation* **2022**, *109*, 102348. [CrossRef]
61. Hayes, P.J. The Frame Problem and Related Problems in Artificial Intelligence. In *Readings in Artificial Intelligence*; Elsevier: Amsterdam, The Netherlands, 1981; pp. 223–230.
62. Rana, N.P.; Chatterjee, S.; Dwivedi, Y.K.; Akter, S. Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. *Eur. J. Inf. Syst.* **2021**, *2*, 1–24. [CrossRef]
63. Ghahramani, Z. Probabilistic machine learning and artificial intelligence. *Nature* **2015**, *521*, 452–459. [CrossRef]
64. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; Duan, Y.; Dwivedi, R.; Edwards, J.; Eirug, A. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* **2021**, *57*, 101994. [CrossRef]
65. Lin, S.-S.; Shen, S.-L.; Zhou, A.; Xu, Y.-S. Risk assessment and management of excavation system based on fuzzy set theory and machine learning methods. *Autom. Constr.* **2021**, *122*, 103490. [CrossRef]
66. Yu, D.; Xu, Z.; Wang, X. Bibliometric analysis of support vector machines research trend: A case study in China. *Int. J. Mach. Learn. Cybern.* **2020**, *11*, 715–728. [CrossRef]
67. Sun, N.; Morris, J.G.; Xu, J.; Zhu, X.; Xie, M. iCARE: A framework for big data-based banking customer analytics. *IBM J. Res. Dev.* **2014**, *58*, 1–4. [CrossRef]
68. Faust, O.; Hagiwara, Y.; Hong, T.J.; Lih, O.S.; Acharya, U.R. Deep learning for healthcare applications based on physiological signals: A review. *Comput. Methods Programs Biomed.* **2018**, *161*, 1–13. [CrossRef]
69. Sun, X.; Wang, B.; Wang, Z.; Li, H.; Li, H.; Fu, K. Research progress on few-shot learning for remote sensing image interpretation. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2021**, *14*, 2387–2402. [CrossRef]
70. Chen, H.; Luo, X. An automatic literature knowledge graph and reasoning network modeling framework based on ontology and natural language processing. *Adv. Eng. Inform.* **2019**, *42*, 100959. [CrossRef]
71. Mukherjee, S.; Bala, P.K. Detecting sarcasm in customer tweets: An NLP based approach. *Ind. Manag. Data Syst.* **2017**, 10. [CrossRef]
72. Chen, X.; Xie, H.; Wang, F.L.; Liu, Z.; Xu, J.; Hao, T. A bibliometric analysis of natural language processing in medical research. *BMC Med. Inform. Decis. Mak.* **2018**, *18*, 1–14. [CrossRef]
73. Mäntylä, M.V.; Graziotin, D.; Kuutila, M. The evolution of sentiment analysis—A review of research topics, venues, and top cited papers. *Comput. Sci. Rev.* **2018**, *27*, 16–32. [CrossRef]
74. O'Leary, D.E. Massive data language models and conversational artificial intelligence: Emerging issues. *Intell. Syst. Account. Financ. Manag.* **2022**, *29*, 182–198. [CrossRef]

75. Goeldner, M.; Herstatt, C.; Tietze, F. The emergence of care robotics—A patent and publication analysis. *Technol. Forecast. Soc. Chang.* **2015**, *92*, 115–131. [CrossRef]
76. Zyoud, S.H.; Zyoud, A.H. Visualization and Mapping of Knowledge and Science Landscapes in Expert Systems with Applications Journal: A 30 Years' Bibliometric Analysis. *SAGE Open* **2021**, *11*, 21582440211027574. [CrossRef]
77. Gupta, D.; Rani, R. A study of big data evolution and research challenges. *J. Inf. Sci.* **2019**, *45*, 322–340. [CrossRef]
78. Bi, Z.; Cochran, D. Big data analytics with applications. *J. Manag. Anal.* **2014**, *1*, 249–265. [CrossRef]
79. Gandomi, A.; Haider, M. Beyond the hype: Big data concepts, methods, and analytics. *Int. J. Inf. Manag.* **2015**, *35*, 137–144. [CrossRef]
80. Yaqoob, I.; Hashem, I.A.T.; Gani, A.; Mokhtar, S.; Ahmed, E.; Anuar, N.B.; Vasilakos, A.V. Big data: From beginning to future. *Int. J. Inf. Manag.* **2016**, *36*, 1231–1247. [CrossRef]
81. Hashem, I.A.T.; Chang, V.; Anuar, N.B.; Adewole, K.; Yaqoob, I.; Gani, A.; Ahmed, E.; Chiroma, H. The role of big data in smart city. *Int. J. Inf. Manag.* **2016**, *36*, 748–758. [CrossRef]
82. Rialti, R.; Marzi, G.; Ciappei, C.; Busso, D. Big data and dynamic capabilities: A bibliometric analysis and systematic literature review. *Manag. Decis.* **2019**, *57*, 2052–2068. [CrossRef]
83. Bendre, M.R.; Thool, V.R. Analytics, challenges and applications in big data environment: A survey. *J. Manag. Anal.* **2016**, *3*, 206–239. [CrossRef]
84. Chong, D.; Shi, H. Big data analytics: A literature review. *J. Manag. Anal.* **2015**, *2*, 175–201. [CrossRef]
85. Elgendy, N.; Elragal, A. Big data analytics: A literature review paper. In *Proceedings of the Industrial Conference on Data Mining*; Springer: Cham, Switzerland, 2014; pp. 214–227.
86. LaValle, S.; Lesser, E.; Shockley, R.; Hopkins, M.S.; Kruschwitz, N. Big data, analytics and the path from insights to value. *MIT Sloan Manag. Rev.* **2011**, *52*, 21–32.
87. Nicolae, B.; Moise, D.; Antoniu, G.; Bougé, L.; Dorier, M. BlobSeer: Bringing high throughput under heavy concurrency to Hadoop Map-Reduce applications. In Proceedings of the 2010 IEEE International Symposium on Parallel & Distributed Processing (IPDPS), Atlanta, GA, USA, 19–23 April 2010; pp. 1–11.
88. Dean, J.; Ghemawat, S. MapReduce: Simplified data processing on large clusters. *Commun. ACM* **2008**, *51*, 107–113. [CrossRef]
89. Kang, Y.-S.; Park, I.-H.; Rhee, J.; Lee, Y.-H. MongoDB-based repository design for IoT-generated RFID/sensor big data. *IEEE Sens. J.* **2015**, *16*, 485–497. [CrossRef]
90. Lv, Z.; Li, X.; Zhang, B.; Wang, W.; Zhu, Y.; Hu, J.; Feng, S. Managing big city information based on WebVRGIS. *IEEE Access* **2016**, *4*, 407–415. [CrossRef]
91. Chan, Y.-Y.; Qu, H. Finavistory: Using Narrative Visualization to Explain Social and Economic Relationships in Financial News. In Proceedings of the 2016 International Conference on Big Data and Smart Computing (BigComp), Hong Kong, China, 18–20 January 2016; pp. 32–39.
92. Archenaa, J.; Anita, E.M. A survey of big data analytics in healthcare and government. *Procedia Comput. Sci.* **2015**, *50*, 408–413. [CrossRef]
93. dos Santos, B.S.; Steiner, M.T.A.; Fenerich, A.T.; Lima, R.H.P. Data mining and machine learning techniques applied to public health problems: A bibliometric analysis from 2009 to 2018. *Comput. Ind. Eng.* **2019**, *138*, 106120. [CrossRef]
94. Gu, D.; Li, J.; Li, X.; Liang, C. Visualizing the knowledge structure and evolution of big data research in healthcare informatics. *Int. J. Med. Inform.* **2017**, *98*, 22–32. [CrossRef]
95. Kim, G.-H.; Trimi, S.; Chung, J.-H. Big-data applications in the government sector. *Commun. ACM* **2014**, *57*, 78–85. [CrossRef]
96. Rajagopalan, M.; Vellaipandiyan, S. Big Data Framework for National E-Governance Plan. In Proceedings of the 2013 Eleventh International Conference on ICT and Knowledge Engineering, Bangkok, Thailand, 20–22 November 2013; pp. 1–5.
97. Ravi, V.; Kamaruddin, S. Big data analytics enabled smart financial services: Opportunities and challenges. In *Proceedings of the International Conference on Big Data Analytics*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 15–39.
98. Fang, B.; Zhang, P. Big Data in Finance. In *Big Data Concepts, Theories, And Applications*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 391–412.
99. Herrmann, H.; Masawi, B. Three and a half decades of artificial intelligence in banking, financial services, and insurance: A systematic evolutionary review. *Strateg. Chang.* **2022**, *31*, 549–569. [CrossRef]
100. Berthelé, E. Using big data in insurance. *Big Data Insur. Co.* **2018**, *1*, 131–161.
101. Kaswan, K.S.; Dhatterwal, J.S.; Sharma, H.; Sood, K. Big Data in Insurance Innovation. In *Big Data: A Game Changer for Insurance Industry*; Sood, K., Dhanaraj, R.K., Balusamy, B., Grima, S., Uma Maheshwari, R., Eds.; Emerald Publishing Limited: Bingley, UK, 2022; pp. 117–136.
102. Corlosquet-Habart, M.; Janssen, J. *Big Data for Insurance Companies*; John Wiley & Sons: London, UK, 2018.
103. Ahmed, S.; Alshater, M.M.; El Ammari, A.; Hammami, H. Artificial intelligence and machine learning in finance: A bibliometric review. *Res. Int. Bus. Financ.* **2022**, *61*, 101646. [CrossRef]
104. Pritchard, A. Statistical bibliography or bibliometrics. *J. Doc.* **1969**, *25*, 348.
105. Linnenluecke, M.K.; Marrone, M.; Singh, A.K. Conducting systematic literature reviews and bibliometric analyses. *Aust. J. Manag.* **2020**, *45*, 175–194. [CrossRef]
106. Moed, H.F.; Burger, W.; Frankfort, J.; Van Raan, A.F. The use of bibliometric data for the measurement of university research performance. *Res. Policy* **1985**, *14*, 131–149. [CrossRef]

107. Aria, M.; Cuccurullo, C. bibliometrix: An R-tool for comprehensive science mapping analysis. *J. Informetr.* **2017**, *11*, 959–975. [CrossRef]
108. Mishra, D.; Gunasekaran, A.; Papadopoulos, T.; Childe, S.J. Big Data and supply chain management: A review and bibliometric analysis. *Ann. Oper. Res.* **2018**, *270*, 313–336. [CrossRef]
109. Jin, R.; Zou, P.X.; Piroozfar, P.; Wood, H.; Yang, Y.; Yan, L.; Han, Y. A science mapping approach based review of construction safety research. *Saf. Sci.* **2019**, *113*, 285–297. [CrossRef]
110. Manesh, M.F.; Pellegrini, M.M.; Marzi, G.; Dabic, M. Knowledge management in the fourth industrial revolution: Mapping the literature and scoping future avenues. *IEEE Trans. Eng. Manag.* **2020**, *68*, 289–300. [CrossRef]
111. Wamba, S.F.; Mishra, D. Big data integration with business processes: A literature review. *Bus. Process Manag. J.* **2017**, *23*, 477–492. [CrossRef]
112. Hinojo-Lucena, F.-J.; Aznar-Díaz, I.; Cáceres-Reche, M.-P.; Romero-Rodríguez, J.-M. Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Educ. Sci.* **2019**, *9*, 51. [CrossRef]
113. Zhang, Y.; Chen, H.; Lu, J.; Zhang, G. Detecting and predicting the topic change of Knowledge-based Systems: A topic-based bibliometric analysis from 1991 to 2016. *Knowl. Based Syst.* **2017**, *133*, 255–268. [CrossRef]
114. Bresciani, S.; Ciampi, F.; Meli, F.; Ferraris, A. Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda. *Int. J. Inf. Manag.* **2021**, *60*, 102347. [CrossRef]
115. Yin, X.; Liu, H.; Chen, Y.; Al-Hussein, M. Building information modelling for off-site construction: Review and future directions. *Autom. Constr.* **2019**, *101*, 72–91. [CrossRef]
116. Kaffash, S.; Nguyen, A.T.; Zhu, J. Big data algorithms and applications in intelligent transportation system: A review and bibliometric analysis. *Int. J. Prod. Econ.* **2021**, *231*, 107868. [CrossRef]
117. Niu, J.; Tang, W.; Xu, F.; Zhou, X.; Song, Y. Global research on artificial intelligence from 1990–2014: Spatially-explicit bibliometric analysis. *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 66. [CrossRef]
118. Forcael, E.; Ferrari, I.; Opazo-Vega, A.; Pulido-Arcas, J.A. Construction 4.0: A literature review. *Sustainability* **2020**, *12*, 9755. [CrossRef]
119. Munawar, H.S.; Qayyum, S.; Ullah, F.; Sepasgozar, S. Big data and its applications in smart real estate and the disaster management life cycle: A systematic analysis. *Big Data Cogn. Comput.* **2020**, *4*, 4. [CrossRef]
120. Osarogiagbon, A.U.; Khan, F.; Venkatesan, R.; Gillard, P. Review and analysis of supervised machine learning algorithms for hazardous events in drilling operations. *Process Saf. Environ. Prot.* **2021**, *147*, 367–384. [CrossRef]
121. Tran, B.X.; McIntyre, R.S.; Latkin, C.A.; Phan, H.T.; Vu, G.T.; Nguyen, H.L.T.; Gwee, K.K.; Ho, C.S.; Ho, R.C. The current research landscape on the artificial intelligence application in the management of depressive disorders: A bibliometric analysis. *Int. J. Environ. Res. Public Health* **2019**, *16*, 2150. [CrossRef]
122. Zhao, L.; Dai, T.; Qiao, Z.; Sun, P.; Hao, J.; Yang, Y. Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Saf. Environ. Prot.* **2020**, *133*, 169–182. [CrossRef]
123. Khudzari, J.M.; Kurian, J.; Tartakovsky, B.; Raghavan, G.V. Bibliometric analysis of global research trends on microbial fuel cells using Scopus database. *Biochem. Eng. J.* **2018**, *136*, 51–60. [CrossRef]
124. Quer, G.; Arnaout, R.; Henne, M.; Arnaout, R. Machine learning and the future of cardiovascular care: JACC state-of-the-art review. *J. Am. Coll. Cardiol.* **2021**, *77*, 300–313. [CrossRef]
125. Takahashi, R.; Kajikawa, Y. Computer-aided diagnosis: A survey with bibliometric analysis. *Int. J. Med. Inform.* **2017**, *101*, 58–67. [CrossRef] [PubMed]
126. Gu, D.; Li, T.; Wang, X.; Yang, X.; Yu, Z. Visualizing the intellectual structure and evolution of electronic health and telemedicine research. *Int. J. Med. Inform.* **2019**, *130*, 103947. [CrossRef]
127. Bao, G.; Fang, H.; Chen, L.; Wan, Y.; Xu, F.; Yang, Q.; Zhang, L. Soft robotics: Academic insights and perspectives through bibliometric analysis. *Soft Robot.* **2018**, *5*, 229–241. [CrossRef]
128. Muhuri, P.K.; Shukla, A.K.; Abraham, A. Industry 4.0: A bibliometric analysis and detailed overview. *Eng. Appl. Artif. Intell.* **2019**, *78*, 218–235. [CrossRef]
129. Nobre, G.C.; Tavares, E. Scientific literature analysis on big data and internet of things applications on circular economy: A bibliometric study. *Scientometrics* **2017**, *111*, 463–492. [CrossRef]
130. Tseng, M.-L.; Tran, T.P.T.; Ha, H.M.; Bui, T.-D.; Lim, M.K. Sustainable industrial and operation engineering trends and challenges Toward Industry 4.0: A data driven analysis. *J. Ind. Prod. Eng.* **2021**, *38*, 581–598. [CrossRef]
131. Kipper, L.M.; Furstenau, L.B.; Hoppe, D.; Frozza, R.; Iepsen, S. Scopus scientific mapping production in industry 4.0 (2011–2018): A bibliometric analysis. *Int. J. Prod. Res.* **2020**, *58*, 1605–1627. [CrossRef]
132. Munim, Z.H.; Dushenko, M.; Jimenez, V.J.; Shakil, M.H.; Imset, M. Big data and artificial intelligence in the maritime industry: A bibliometric review and future research directions. *Marit. Policy Manag.* **2020**, *47*, 577–597. [CrossRef]
133. Nusair, K. Developing a comprehensive life cycle framework for social media research in hospitality and tourism. *Int. J. Contemp. Hosp. Manag.* **2020**, *32*, 1041–1066. [CrossRef]
134. Nusair, K.; Butt, I.; Nikhashemi, S.R. A bibliometric analysis of social media in hospitality and tourism research. *Int. J. Contemp. Hosp. Manag.* **2019**, *31*, 2691–2719. [CrossRef]

135. Liu, H.; Liu, Y.; Wang, Y.; Pan, C. Hot topics and emerging trends in tourism forecasting research: A scientometric review. *Tour. Econ.* **2019**, *25*, 448–468. [CrossRef]
136. Prado, J.W.; Castro Alcântara, V.; Melo Carvalho, F.; Vieira, K.C.; Machado, L.K.; Tonelli, D.F. Multivariate analysis of credit risk and bankruptcy research data: A bibliometric study involving different knowledge fields (1968–2014). *Scientometrics* **2016**, *106*, 1007–1029. [CrossRef]
137. Riahi, Y.; Saikouk, T.; Gunasekaran, A.; Badraoui, I. Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Syst. Appl.* **2021**, *173*, 114702. [CrossRef]
138. Hu, H.; Wen, Y.; Chua, T.-S.; Li, X. Toward scalable systems for big data analytics: A technology tutorial. *IEEE Access* **2014**, *2*, 652–687. [CrossRef]
139. Siemens, G. Learning analytics: The emergence of a discipline. *Am. Behav. Sci.* **2013**, *57*, 1380–1400. [CrossRef]