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Strategic Key Elements in Big Data Analytics as Driving Forces of IoT Manufacturing Value Creation: A Challenge for Research Framework

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***Abstract*—Big Data (BD)-driven business intelligence (BI) is considered to be a new development stage within industrial engineering management to achieve higher business value creation. The article provides extensive research of BD-driven approaches to identify strategic knowledge and value-creating components within Internet of Things (IoT) manufacturing. Due to previous research studies focused mostly on partial solutions and lack a holistic view, this article topic is still far from being sufficiently explored and resolved. The article presents the results of an extensive research study of contemporary professional literature with a specific aim to provide a more holistic and systematical view on the current state and future trends in this issue. To solve this high complex research problem, both quantitative and qualitative research methodology approaches are used. The article is primarily based on a systematic literature review covering 187 essential and 36 additional current research papers within the Web of Science and Scopus database from 2012 to the present. Research findings identify the seven key strategic elements determining that Big Data analytics (BDA) can become a real and tremendous business value creation driver within IoT intelligent manufacturing. These research results provide important conclusions and implications for challenging future investigations into BDA and BI systems in the context of advancing the Industry 4.0 revolution. In conclusion, we propose a final suggestion in the form of a strategic future research chain from IoT through BDA to value creation based on BD intelligence within IoT manufacturing, whereas seven strategic elements might play a crucial.**

***Index Terms*—Big Data analytics (BDA), business intelligence (BI), business performance, cyber-physical production systems, Industry 4.0, intelligent manufacturing, Internet of Things (IoT), knowledge information systems, knowledge management, planning and scheduling, value creation.**

I. Introduction

BASED on initial analysis of the literature, we can draw a preliminary outline, whose components we intend role to explore, and presume that the IoT technologies with real-time big data analytics (BDA) and real-time-based process elements are the main potential directions of future research in order to capture the business and big data (BD) value and consequently create a higher value, business growth, and competitive advantage within IoT manufacturing (see Fig. 1).

Due to the enormous complexity of the research problem, Fig. 1 is to be found right in the introduction with the aim so far only schematically to define a research framework of further extensive research while more detailed approaches and their results are presented in the following chapters. We are aware that the information captured in this figure is still introductory, quite theoretical, and static. However, in the following sections, we gradually bring research results that provide more dynamics and higher added value to the knowledge within IoT manufacturing theory and practice.

From literature in general, the most emphasized components to transform the Industry 4.0 driven companies are the utilization of smart technologies to achieve real-time BD processing to gain higher value creation and competitive advantage through growth and knowledge (see Fig. 1 below).

Therefore, we are primarily concerned with BDA in the IoT regarding value creation, business performance, and knowledge information systems. The accuracy of this primary orientation in solving research problems can be confirmed by many authors of recent literature [1]–[8]. According to Sjödin *et al.*, in order to optimize IoT manufacturing processes, it is paramount to effectively employ BDA technologies [8]. Furthermore, data-driven decision-making business intelligence (BI) and analytics can create competitive advantages for organizations, given that they are used effectively [9]–[13]. Moreover, as Thirathon *et al.* [14] stated, managers with sophisticated BDA systems are more likely to base their decisions on sufficient evidence. Also, Astill *et al.* [15] declare that BDA technology will simplify extracting relevant information that endorses decision-making. According to the survey conducted in Chinese companies, the article showed that there is a link between BDA capability and business performance [16].

Based on the above mentioned, we presume that in the future, managerial information support will have to be able to process a lot of distinguished data to capture a higher value and knowledge. However, as Roberts and Laramee state, a challenging task is to capture all the value from the data [17]. Also, according to Olszak and Zurada even though BDA topics

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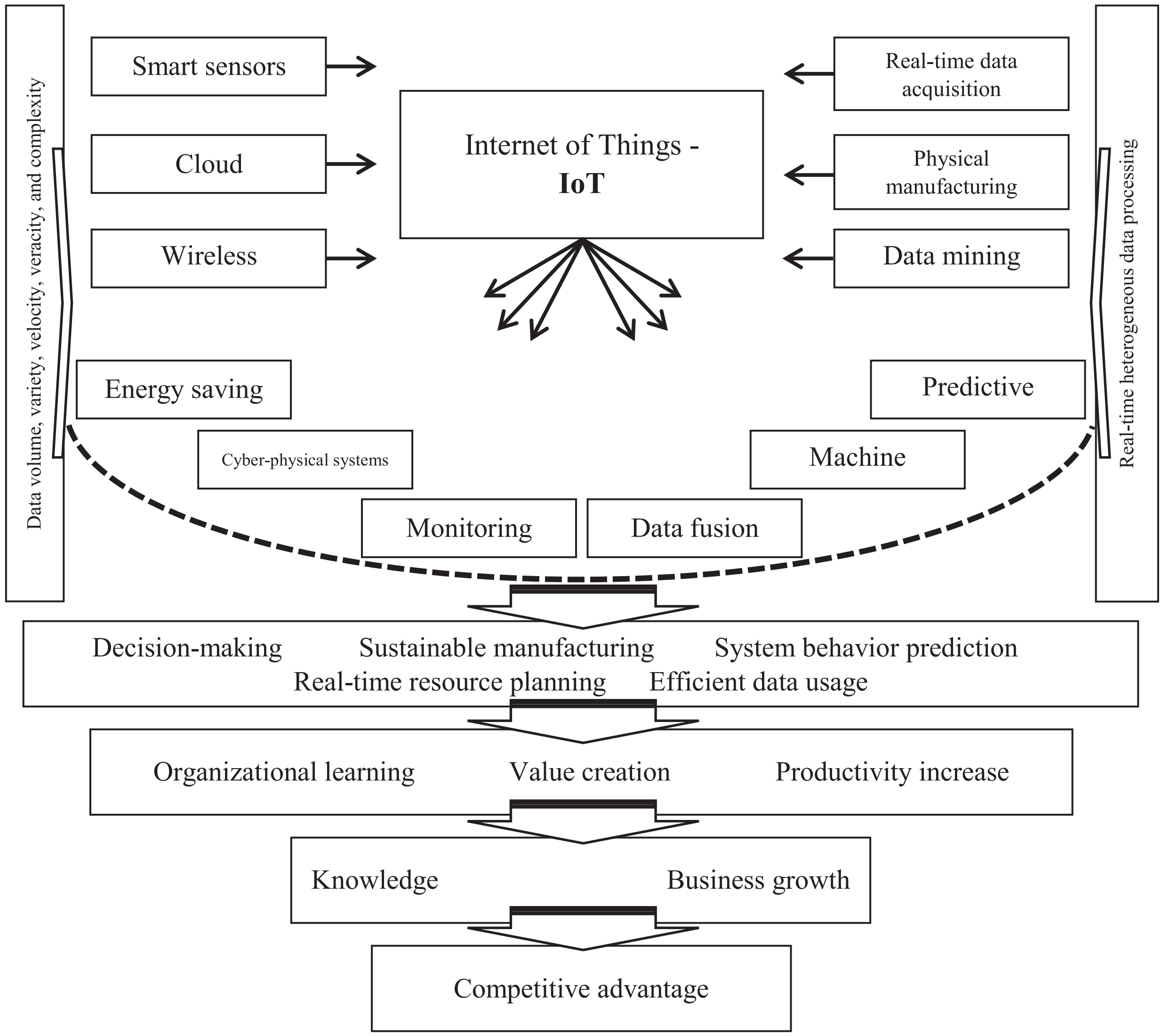

Fig. 1. BDA-based value creation as a driving force of IoT manufacturing—an initial research framework (source: own).

are becoming more researched over the years, there is still a lack of comprehensive research concerning BD and value creation [18]. There are still opportunities to explore new indicators and methodologies to efficiently demonstrate the application of value creation through BDA, as stated by Furtado *et al.* [19]. As also confirmed by Popovič *et al.* [20], the BDA and its effect on business performance will not be exploited entirely without more knowledge of BDA in operations. A recent research study provided by Bordeleau *et al.* [21] in manufacturing medium enterprises displays that it may be demanding to control individual processes performance concerning capturing data value. Once the availability of data increases, a business will incline to employ the potential of data visualization [17], i.e., Xu *et al.* [22] present a paper of a real-time production data tracking visualization in Bosch Plant in the USA. Moreover, according to Marjani *et al.* [23], most BD visualization tools used for the IoT perform poor results in terms of functionality, scalability, and response time.

Taking into account the abovementioned, this article topic is still far from being sufficiently explored and resolved, which also in data analytics value creation in general remains still an open research problem and a practical challenge [24]. It is clear that these studies have focused so far only on partial solutions to this research problem and lack a holistic view. These previous studies and a lack of comprehensive research concerning BDA and value creation, also declared in recent research by Olszak and Zurada [18], were an initial motivation to realize this comprehensive research study to fill this research gap.

Therefore, based on the all abovementioned, the article aims to present the results of an extensive research study of contemporary professional literature worldwide with a specific aim to provide a more holistic and systematical view on the possible future trends and key components in BDA and knowledge information support systems to achieve higher business value creation within IoT-oriented manufacturing.

In research results (Section IV) based on the methodology set in the previous Section III (Material and Methods), we identify the key BDA research categories, namely to which primary utilization and process factors, technologies, and managerial tools are concerned so that we are able to determine the strategic

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key elements in connection to BDA and value creation within IoT intelligent manufacturing. The findings of this extensive research study furthermore indicate that future researches will be concerned with further examination of IoT intelligent manufacturing in the sense of data-driven manufacturing, multisource heterogeneous BD processing, and cyber-physical systems data processing. Finally, and following previous partial research results, also BD integration, prediction, and visualization together with real-time autonomous production planning present more investigation challenges to create the higher business value of IoT intelligent manufacturing through BDA-based knowledge generation. Based on these research results and key findings, the previously identified research gap, questions, and hypothesis evaluated, we conclude that this challenging research study provides possible directions for future academic research and practice.

II. Literature Review

After the previous introductory part, where we clarify the research topic and outline a research gap using the results from some previous research studies and real practice examples, in this section, we present a more comprehensive literature review, inquiring closer into BDA in general, and also specifically in the BDA-related technologies and their impact on value creation in the Industry 4.0 intelligent manufacturing. This literature review is to determine the basis for the specific research framework identified in the material and methods (Section III). Due to the high complexity of the research topic, we further continually pursue our main research goal mentioned above and analyze the BDA in general and also in the context of business value creation within IoT manufacturing.

Concerning Fig. 1 as an initial research framework (see above), identifying BD in general and also its utilization in the BDA technologies up to covering their impact on the value creation within data-driven IoT intelligent manufacturing are deeper analyzed. Therefore, based on the primary research goal and this initial research framework shown in Fig. 1, we divided this chapter into three partial subsections (see below) to define the three main research questions and hypothesis. In the final part of this Section II (Literature Review), we also examine the current literature in terms of the methodological approaches used in previous research on this topic.

Due to the already mentioned complexity of the research problem and nature of the proposed research methodology (see Section III), the intention of this section is not to provide an extensive literature review mostly typical for other researches, but rather to create a sufficiently base for subsequent extensive and systematical research study presented in the following sections of the article.

A. *Big Data Analytics—A Brief General Overview*

Many authors define BD generally with characteristics as high volume, velocity, and variety together with analytical methods and data transformation into a value with its specific challenges including heterogeneous communication, integration, and data extraction [2], [23], [25]–[28]. According to Agarwal and Dhar, BD aims at the right person at the right time in the right form, but in a significantly sophisticated form than it did in the past [29]. In addition to this, the term BDA is a more complex process to enhance business value and foster growth [2]–[4], [30]–[32]. Data analysis in the traditional point of view was defined as obtaining knowledge from information gained by studying, organizing, reaching conclusions, and sometimes making predictions from the data [33]. Opposite to this, BDA consists of normalizing, verifying, filtering, compressing, and analyzing vast amounts of collected data [34]. Therefore, in contrast to the traditional point of view, a variety, storage, integration, and processing of amounts of collected data belong among challenges in BD management [35], [36]. Some researchers argue that all dimensions of BDA competency (data quality, analytical skills, domain knowledge, tools sophistication, and bigness of data) have a significant effect on decision quality [37], [38]. Demirkan and Delen [39] state that once data, information, and analytics have been defined, one can observe that the traditional measurement mechanisms do not work efficiently in terms of decision support systems.

Moreover, the modern trends also incorporate cloud-based BDA solutions [40], [41]. Related to cloud computing, BD processed in various solutions may be descriptive, prescriptive, or predictive [35].

B. *BDA Impact on Performance and Value Creation Within IoT Manufacturing*

BD analytics technologies pose additional software and infrastructure costs concerning IoT [35]. With the surge of the vast data volumes using of 5G network, currently employed approaches are becoming ineffective in terms of scalability, cost, and flexibility [42]. However, the Industry 4.0 concept requires high system flexibility, speed, and quality, so that technologies such as the IoT or cyber-physical systems could work effectively [43]. The focus of the computer science and engineering literature is on developing predictive informatics tools to manage BD in IoT manufacturing [44].

A necessary step forward is to employ Industry 4.0 technologies in reality [45]. Wang *et al.* [46] clarify a recent term of deep learning and state that deep learning advances analytical tools, algorithms, technologies for processing BD. Moreover, data profiling tools are available for both small and comprehensive data processing [47]. It is evident that the IoT will play an important role in the near future in establishing infrastructure and the deployment of related informatics technology devices, including BDA [44]. According to Siow *et al.* [48], the greatest challenges nowadays in BD analytics within IoT reside in finding tradeoffs between analytical value, performance, and distribution of the vast data variety. Phillips-Wren *et al.* [11] state that data-driven decision-making Business Intelligence and Analytics (BI&A) and BD can create competitive advantages and business value in IoT.

According to the research realized in American companies, BDA provides two major effects on supply chain value creation: value productivity and business growth [49]. Moreover, according to Dubey *et al.*, [50] world-class manufacturing companies

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benefit from BDA with superior economic, social, and environmental performance. Information from BD can improve corporate social performance and these improvements occur through organizational innovation in business practices [51]. Compared to this, the term of wisdom manufacturing used by Yao *et al.* [52] incorporates social computing, crowdsourcing, customization, sustainability, and innovation promotion in manufacturing.

On the other side, Zhou *et al.* [53] state that in terms of saving data, there is still potential regarding the issue of energy-saving BD. Some may include the speed of collecting, processing, and using energy data, even data integration. BDA-based software may function as cost-based optimizers and can execute scheduling, network data transfers, or fault tolerance [54]. An empirical analysis provided in German-speaking countries by Wiech *et al.* [7] suggests that BDA helps companies achieve both product enhancing and internal process performance but has no significant effect on overall business performance.

BI and other BDA tools are utilized with higher business performance companies [50], [55]. Some authors suggest that future researches are to be focused on both automation and real-time processing of huge-variety BD and their effect on decision-making and costs [56], [57].

C. Big Data-Driven Intelligent IoT Manufacturing

According to Zhong *et al.* [58], future perspectives in Industry 4.0 are as follows: generic framework for intelligent manufacturing incorporating smart design, smart machines, smart monitoring, smart control, and smart scheduling; data-driven intelligent manufacturing models; intelligent manufacturing systems; human–machine collaboration; and application of intelligent manufacturing.

The utilization of real-time information is most likely going to be in the lead of Industry 4.0 [59]. However, nowadays, centralized approaches are conducted offline for data computing. Centralized algorithms can employ global information to support scheduling but often encounter difficulties for a real-time response [60].

Zhong *et al.* [58] and also Oztemel and Gursev [59] define future perspectives in data-driven intelligent manufacturing as follows: data-driven intelligent manufacturing models using, i.e., RFID sensors increasing the quality and efficiency in production, intelligent manufacturing systems employing cloud technologies, human–machine collaboration, and application of intelligent manufacturing. Kang *et al.* [61] suggest IoT with regard to smart factories incorporating smart logistics, smart buildings, smart products, smart grids, and smart mobility. The authors define the IoT as the core technology for smart manufacturing in all researched regions; Germany, the USA, and South Korea. Moreover, there are two main challenges to overcome regarding processing BD; technology implementation with necessary organizational changes and the process should be created to support peoples' activities and positively affect their work, as proposed by Poleto *et al.* [62].

Given all the abovementioned in the introductory part and also in Section II, we can conclude that from the previous article, there remains an urgent research gap. In contrast, they have dealt mostly with partial questions of this a considerably high complex research problem. So there is still a research gap that has already been outlined in the introductory part of this article. Based on this and together with parallel pursuing the main research goal, we can fix our research direction in the form of this main strategic research chain to fill this rather significant research gap: *from IoT– through BDA– to value creation based on Big Data Intelligence within IoT manufacturing*, while from literature review, it appears that the term "BDA" might be considered as a keyword to higher value creation within IoT intelligent manufacturing.

Therefore, to solve this challenging research problem and fill the research gap, we have proposed the following three main research questions (hypotheses):

> *H1:* BDA presents a high important research topic within current academic research worldwide in several research areas and categories. We assume that one of these is also IoT intelligent (smart) manufacturing area.
>
> *H2:* We assume that in these selected research areas and categories, it is possible to identify common factors such as research topics, technologies, and managerial tools directly related to BDA as the key elements of the business value creation.
>
> *H3:* Based on this, we assume that these identified key elements can be considered as strategic key elements in value creation also within IoT intelligent manufacturing.

In addition to the above, we also performed a literature review concerning the methodological approaches used to answer these research questions and hypotheses.

There are a few recent research studies provided by a systematic literature review methodological approach [1]–[3], [6], [11], [25], [32], [59], [63]–[65]. We have found a systematic literature review that has recently been conducted by Mikalef *et al.* helping to explain the mechanisms through which BDA lead to competitive performance gains [64]. This article proposes six main themes for future research as being strategic to gain competitive performance and higher business value, namely BDA's resources, capability, rationality, turning into action, trust of top managers, and business value measurement. In addition, this article also identified an urgent need to examine BDA through a holistic approach. According to Günther *et al.*, realizing value from BD is the result of continuous interaction between work practices, organizational models, and stakeholder interests, and call for empirical research on cross-level interactions and alignment [63]. In another article published by Alizadeh *et al.* [65], the biofuels are explored to draw the state-of-the-art for future-oriented biofuel research. A six-fold typology mapping from two main future studies methodologies was used. This research method also appears quite suitable, but its use is out of our primary research topic.

Other recent research conducted by Zhou *et al.* [66] introduces relevant aspects of Industry 4.0 smart factory and intelligent production concerning strategic planning, key technologies, opportunities, and challenges and their horizontal, vertical, and end-to-end integration discussing main challenges such as the development of smart devices, the construction of the network environment, BD analysis and processing, and digital production. Unfortunately, this article is provided mostly in an informative and descriptive approach. Similarly, only qualitative and

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descriptive approaches were used by Tao *et al.* [67] to define a decisive data-driven smart manufacturing application.

The research article also published recently by Horváth and Szabó [68] aimed to explore how top executives interpret the driving forces for introducing new technologies and the main barriers to Industry 4.0. The authors found that management's desire to increase control and enable real-time performance measurement is a significant driving force behind Industry 4.0. However, the authors applied only a qualitative case study design involving semi-structured interviews with 26 leading members of firms.

The analysis of a series of case studies provided by Roden *et al.* [69] examines the role of BD in affecting the core dimensions of an operations model (namely capacity, supply network, process and technology, and people development and organization) in order to generate higher value.

Another interesting research was provided by Alizadeh *et al.* [70] to evaluate the performance of complex electricity generation systems. The network-based DEA (data envelopment analysis) method was built to determine the efficacy of this system. Although the DEA method appears to be quite a holistic research approach, the area of research in which it has been used is not sufficiently consistent with our topic of interest.

Based on the abovementioned, we can conclude that also concerning methodological approaches to solving the researched problem, there is an additional sufficiently challenging research gap.

III. Material and Methods

The main objective (see also Section I) of this both quantitative and qualitative research study to fulfilling the research gap is to systematically analyze academic research topics and the direction of recent findings in the area of BI and BDA based knowledge information systems that might be used in the near future to generate higher business value, knowledge, and competitive advantage in IoT intelligent manufacturing. Subsequently, we try to identify the strategic key elements in BDA as driving forces within IoT manufacturing value creation.

In order to fill this research gap and goal and conduct this extensive research study, we employed a holistic approach using systematic both qualitative and quantitative methods to analyze the research articles published in the most significant academic journals (according to Impact Factor established by Clarivate Analytics Journal Citation Report) in the Web of Science and Scopus database (according to SJR indicator—Scimago Journal and Country Rank) over the recent period (from 2012 until present).

The research methods were used, following key methodical approaches and limitations published in the previous research. According to Tranfield *et al.* [71], the systematic research review is defined as finding the objective and relevant conclusion about a given topic. Researches without proper evidence lack both relevance and rigor without synthesizing the findings. Becheikh *et al.* [72] state that the first step of the systematic study is to identify individual factors by first defining the targeted group of research sources, eliminating undesirable sources, and further reviewing retrieved studies that meet the criteria. Booth *et al.* [73] declare that systematic researches reduce the possibility of bias within a review. In the phase of gathering sources, the articles with appropriate abstracts, which indicate that they are relevant to our research topic in the Industry 4.0 context, are selected to be further analyzed [74]. The following clustering refined results might guide other studies by identifying gaps in the research papers [75].

The systematic literature analysis considers the main aim of the article so that the articles might be categorized depending on the keywords, the abstract, and the release year. Given the previous literature review and the main research goal, the term "BDA" appears to be a keyword to higher value creation in IoT intelligent manufacturing.

The research study was realized in the six main stages (see Fig. 2). These individual stages are characterized below.

The research data were collected in the form of research papers, in which the key term "BDA" is the most relevant topic in the Web of Science and Scopus papers as source databases published to the present with the number of citations exceeding 100. The search was filtered only by the most cited criterion, then further inquiring into the objectives and directions of the selected areas and synthesizing the individual classifications. The term "BDA" was chosen as a keyword to search published articles sorted by cited times and collected by Web of Science with the article count of over 5100 results and the Scopus database containing as many as 5000 results. To avoid any bias, we resolved to incorporate papers from both databases.

The first phase (Stage 1) was the base of the literature collection (see Fig. 2). First, 187 papers that have been cited more than 100 times were collected with the alignment of the results by most cited (as a filter factor, total citation count was used). The same criterion was applied in the WoS and Scopus database, excluding the papers that matched to eliminate duplicates. Most of the searched articles were found simultaneously in both the Web of Science and Scopus databases (96 results), 75 result papers were published on the Scopus website only, and 16 exclusively on the Web of Science. For these articles, there were preliminary categories selected (see Table I below) that fitted the research field most accurately. The key term for the research was studied in 187 academic papers registered in the WoS and Scopus databases. Based on the area in which the keyword inquired into in the journal, particular categories were selected (Stage 2).

In the researched article, eight major categories based on their laid foundation in the abstract and their keywords identified, and the number of the results in each year was depicted (see Table I). Among services, articles relating to infrastructure, urbanization, smart city, tourism, education, or astronomy were found. BI inquired into BD and their information support business together with decision making. Industry 4.0 is concerned with smart factory and manufacturing concepts, innovation, Internet of Things, Cloud systems, and 5G network. General overview of BD incorporated studies on data science, general literature reviews, modeling, and usage in companies. The category "other" is comprised of mainly marketing topics or civil engineering.

In another Stage 3, all articles prior to 2012 were excluded from the research. Throughout the study of the current trends and prospects in the literature (100 articles), individual seven state-of-the-art key elements were identified (Stage 4). The

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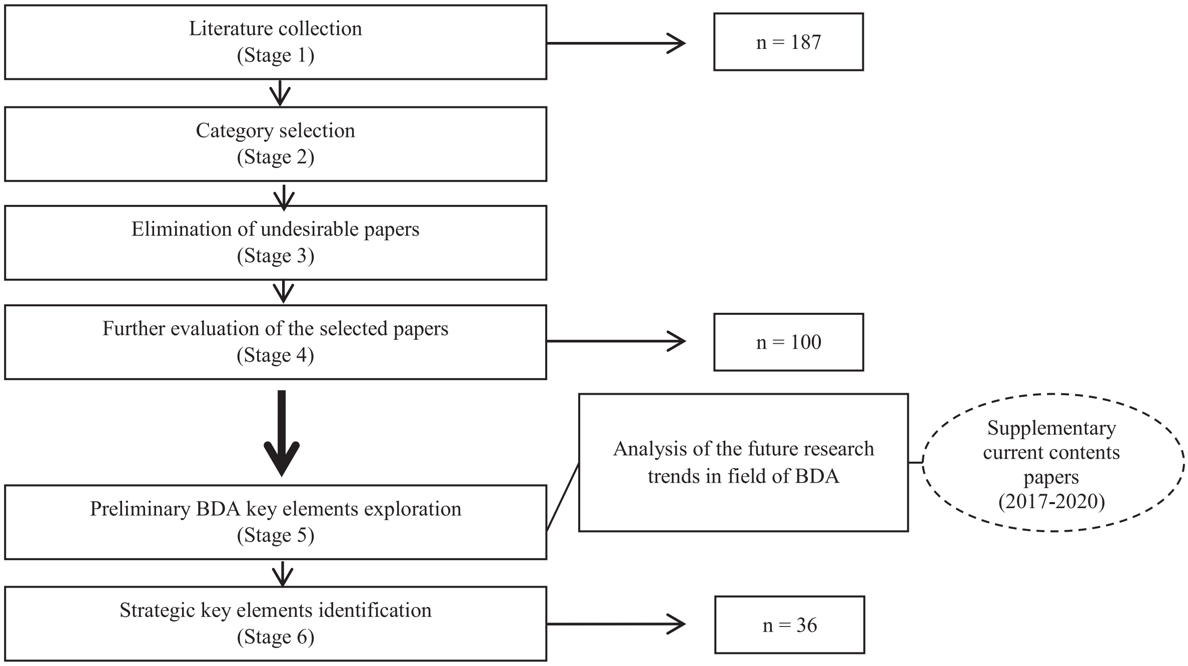

Fig. 2. Search and research process (source: own).

TABLE I
IDENTIFYING RESEARCH CATEGORIES (SOURCE: OWN)

Preliminary categories/ Years	2012	2013	2014	2015	2016	2017	2018	2019
Industry 4.0 (smart manufacturing)	1	2	5	7	8	7	5	2
Big Data (General Overview)	4	3	8	7	4	6	0	0
Business Intelligence	2	2	6	3	2	5	1	0
Services	2	2	9	12	10	6	4	1
Quality	0	0	1	4	5	0	0	0
Healthcare	0	0	4	2	6	6	2	0
Logistics	0	1	1	2	1	1	1	1
Other	0	0	5	2	3	3	0	0

abstract, research results, defined methods, technologies, managerial tools, and conclusions were taken into account when analyzing and classifying these seven primary key elements. The research gap in academic literature and future research topics were selected from the current research papers filtered by date mainly from 2017 to 2020 (Stage 5). Finally, 36 individual papers with their findings and future implications were closely analyzed to mediate (so-called pooling approach was used similar to the identification of Covid-19 virus in a specific group of people) the current state and future development of these discovered key elements within IoT intelligent manufacturing (Stage 6).

IV. RESULTS

An overview of the researched articles (including categories) and their count throughout the article was displayed in Table I. Only academic journals that were used more than three times in the first stage (only articles with more than 100 citations) are displayed in Table II. Journal IEEE Access, International Journal of Production Economics, and Journal of Business Research are to be found among the top three academic journals concerned with the BDA-driven IoT in the searched papers. Most research articles were from 30 countries originating in the USA (75), followed by China (21) and the U.K. (10).

A. *Big Data Analytics Penetration*

Over time, BDA has become a stable topic in the research worldwide. The research results indicate that BDA is most frequently used in connection to general BD topics, services, and also the Industry 4.0 concept including smart manufacturing (Fig. 3).

Apart from the sole usage of BDA with Industry 4.0, together with BI, logistics, and quality, BDA in connection with Industry 4.0 incorporates 40% of the research papers. Frequent utilization in academic researches may also be found in services (18%), healthcare (11%), or general papers along with the BDA topic (24%). Moreover, we might observe a stable rising trend of BDA usage connected to Industry 4.0, BI, quality, and logistics during the period analyzed (2012–2019). The all-time count of the published articles on the topic "BDA" reached its peak during the period of 2018–2019. The trend appears to have been

TABLE II
MOST USED ACADEMIC JOURNALS IN THE RESEARCH (SOURCE: OWN)

Journal	No. of results
IEEE Access	9
International Journal of Production Economics	8
Journal of Business Research	8
International Journal of Information Management	6
Health Affairs	4
IEEE Network	4
Journal of Big Data	4
Big Data and Society	3
Decision Support Systems	3
Future Generation Computer Systems-the-International Journal of Science	3
IEEE Communications Magazine	3
IEEE Communications Surveys and Tutorials	3
IEEE Systems Journal	3
IEEE Transactions on Industrial Informatics	3
International Journal of Advanced Manufacturing Technology	3
International Journal of Production Research	3

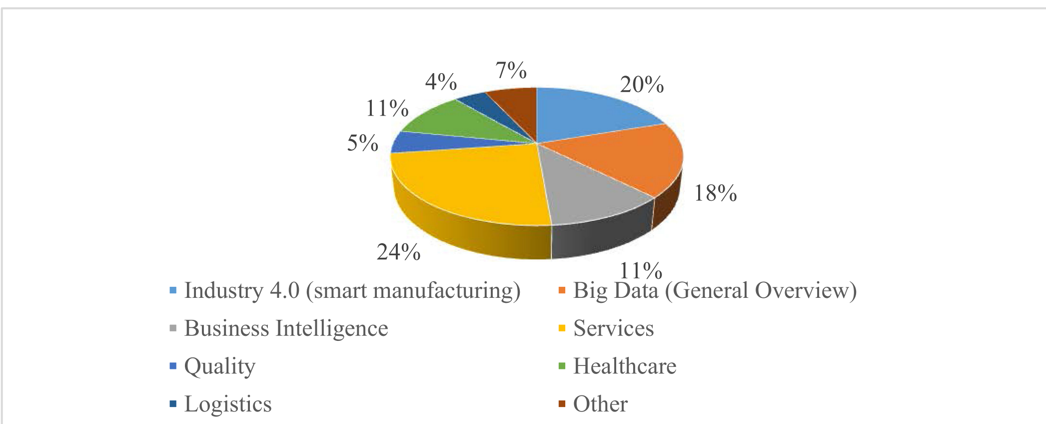

Fig. 3. Division of individual big data analytics fields (source: own).

plummeting since 2018, which we consider acceptable given that the latest academic papers have not had enough time to gain sufficient citation amount (100 citations) as this filter criterion was established in the first stage of the search. In the near future, it is expected that citing papers in the years 2020–2021 and the following years will rise.

B. Big Data Analytics Key Categories, Factors, Technologies, and Managerial Tools

Based on the results mentioned above, in the following Tables III –VI, selected factors such as research topics, technologies, and managerial tools are displayed in four main categories identified in the previous stage. These were chosen from relevant papers after undesirable sources older than 2012 were eliminated (Stage 4). Based on their abstract, research results, conclusion, researched context, managerial and process tools, and technologies, we analyzed the 100 articles. Based on the research results achieved in the previous stages, these four categories were selected: Industry 4.0 (smart manufacturing), BD (general overview), BI, and quality. Mainly due to the fact that the General BD approach is significantly represented in the fourth research stage and together with the smart manufacturing category, articles in these two categories, followed by the BI category, generate most of the IoT-related technologies and methods. Real-time data processing is simultaneously the main interest in many authors' researches.

Selected categories and their factors (meaning the aspect and the context of the research topics) are primarily defined (see Tables III–VI), where possible, managerial tools and technologies were also defined to provide further insight into the depicted factors so that the contemporary strategic key BDA elements of IoT smart manufacturing within the final Stage 6 of our research can be identified.

C. Exploration of Big Data Analytics Key Elements in the Context of Industry 4.0

The final part of this comprehensive and systematic research study includes synthesizing the contemporary academic literature analysis realized in the previous stages and the display of how BDA interconnects different key elements. Fig. 4

TABLE III
INDUSTRY 4.0 SMART MANUFACTURING: KEY CATEGORIES, FACTORS, TECHNOLOGIES, AND MANAGERIAL TOOLS (SOURCE: OWN)

Category	**Factor** (Research topics)	**Technologies, managerial tools**	**References**
Industry 4.0 (smart manufacturing)	Automated real-time monitoring, real-time production management system	IoT, cloud-computing, industrial wireless network, RFID utilization, dynamic demand response, cyber-physical system, data driven manufacturing models	[40], [46], [58], [60], [76], [77], [78]
		Intelligent algorithms, self-aware and self-maintained machines	[73]
		Intelligent manufacturing systems, biological manufacturing systems, manufacturing science and technology, cyber-physical system	[45]
	Autonomous management to effective planning, decision-making support, company performance, visualization, predictive analytics, value creation	Autonomous management to support decision making, company performance, visualization, predictive analytics, value creation	[9], [35], [79]
		Hadoop	[80]
		Cloud computing, stochastic systems, decision-making simulation optimization algorithms	[81]
		Data preprocessing, analytics software	[82]
		Socio-technical feature of big data, organizational models	[63]
	Predictive manufacturing, cyber-physical systems, efficiency increase, 5M system	RFID, prognostics and health management, MTConnect communication protocol	[83]
	3V processing, data mining and storage, data integrity Big Data security, data analytics ecosystem, operation management	IoT, wireless sensor networks, cloud computing, mobile internet, industrial wireless network	[27], [28]
		IoT, RFID, wireless sensor and actor networks, cloud, Lambda Architecture, MySQL, MongoDB, Casandra, SQLite	[84], [85]
		Not available	[86]
		Not available	[87]
	Parallel processing, time/space efficiency	DRAM, relational databases, query processing, HTM, RDMA, NoWQL, NewSQL, NUMA	[88]
		5G network, network virtualization	[89], [90]
	Data dimensionality, scalability, applicability	Not available	[91]
	Machine learning, deep learning, online learning algorithms, deep measuring	5G, mobile packet core networks, Hadoop eco-system	[42]
		IoT, multi-layer perceptron, Spark SQL, Spartk Streaming, GraphX, Hadoop, H2O, Apache SAMOA	[92]
		Neural networks, online learning algorithms, cloud computing, deep learning interfaces, deep learning datasets utilization, deep learning languages	[93]
		Not available	[94]
	Sustainable manufacturing	Total Quality Management, Total Productive Maintenance, lean methods	[50]
		Auto-ID, smart sensor technology	[95]
		Augmented reality, remote maintenance, prognostics, query engine Hive, Mahout, cloud computing, IoT	[96]
		Not available	[97]
	Global value chain, organizational activities, digital technologies utilization	IoT, robotic systems	[98]
	System management, strategic management, new concepts in Industry 4.0	Not available	[99]

TABLE IV
BIG DATA (GENERALLY): KEY CATEGORIES, FACTORS, TECHNOLOGIES, AND MANAGERIAL TOOLS (SOURCE: OWN)

Category	**Factor** (Research topics)	**Technologies, managerial tools**	**References**
BD (generally)	Data quality, data security, access control	Virtual Machine Monitor, Apache, Hadoop	[100]
		Cloud computing, network monitoring	[101]
	Decision making, data acquisition and processing systems	Not available	[102], [103], [104], [105], [106]
		Standard Network Analysis Platform, C++ platform	[107]
		Structure modeling	[108]
		NoSQL, BigQuery, MapReduce, Hadoop, WIBIData, Skytree	[109]
	Data gathering, Big Data capabilities	Not available	[110]
	Deep learning, machine learning, computational power	Mobile big data processing, Apache Spark	[111]
		Not available	[112], [113]
	Predictive analytics	Model optimization and real-time constraints, statistical learning tools, signal processing, principal component analysis, dictionary learning, compressive sampling, subspace clustering, cloud	[114]
		Text analytics (emails, audio, video, social media analytics), predictive analytics	[115]
	Parallel processing, real-time detection, data security, data processing platforms, effective information extraction	Hadoop, Hive, Mahout, Peer-to-Peer	[116], [117]
	Online learning, batch learning methods	Not available	[118]
	Big Data optimization, cost-efficient process	IoT, MapR, Hadoop, LucidWorksSearch, real-time analytics	[119]
	Associating strategy and information practices, environment, social media, online data capturing	RFID, sensor-generated data, log records, CCTV	[120]
	Healthcare, economic productivity, security, innovation, decision making, digitization	Not available	[121]
	Competitive advantage	Sensors, smart phones, RFID, social media	[122]
	Supply chain, organizational performance, visualization, organizational performance, top management commitment	Not available	[123], [124]
	real-time analytics, smart cities, data query, supply chains, smart grid, e-commerce, data mining	IoT, wireless technologies, sensors, social media, health care applications, MapReduce, HANA, Greenplum, Scribe, Kafka, Timetunnel, Chukwa, MongoDB	[23], [125]
	geography data, spatial-temporal data, real-time data, visual data, security, data applications, prediction, smart cities, analysis algorithms	IoT, mobile data, online network, MapReduce	[57]
	Data storage, data monitoring	MySQL	[126]
	BDA general applications, network infrastructure	IoT, Fog Computing, BDA, cloud technologies	[127]
	Convex optimization algorithms for big data, data approximation	Statistical tools	[128]
	Video analytics	Cloud computing, IoT, metropolitan area networks	[129]

TABLE V
BUSINESS INTELLIGENCE (BI): KEY CATEGORIES, FACTORS, TECHNOLOGIES, AND MANAGERIAL TOOLS (SOURCE: OWN)

Category	**Factor** (Research topics)	**Technologies, managerial tools**	**References**
BI	Decision support systems, reporting, visualization	Cloud computing, Information-as-a-service, OLAP, simulation, IoT	[16], [39], [130]
		Big data governance mechanisms	[131]
		Analytics	[132]
		Big data architecture, Hadoop	[133]
		Not available	[134], [135]
	Mobile visualization, sensors, data security, monitoring in financial sectors	OLAP, mobile BI	[136]
	Knowledge from digital datasets, complex data	Data warehouse, software as a service, platform-as-a-service, infrastructure-as-a-service	[137]
		Cloud computing, MapReduce, Hadoop, NoSQL, software as a service, platform-as-a-service, infrastructure-as-a-service	[138]
	Real-time analysis, data acquisition, transmission, storage, and processing	Data analysis applications (MapReduce, Dryad, Pregel, Dremel), NoSQl STORES, Hadoop	[139], [140]
		System modeling, parallel data analysis	[54]
	Value creation, organizational growth	Not available	[49]
	Business analytics and decision support systems	BI ERP extensions	[141]
	Technological capabilities to succeed with Big Data, the role of management in Big Data, BDA effect on firm performance	Not available	[142]
	Agile BI framework, data acquisition, Big Data Analysis and visualization, data validation and deployment	Not available	[143]
	Strategic performance, financial performance, competitive advantage agility, value creation, data quality	Not available	[144], [145]

TABLE VI
QUALITY: KEY CATEGORIES, FACTORS, TECHNOLOGIES, AND MANAGERIAL TOOLS (SOURCE: OWN)

Category	**Factor** (Research topics)	**Technologies, managerial tools**	**References**
Quality	Data quality, IT capability	Not available	[146]
	Product lifecycle management efficiency	RFID, social networks	[36]
	Material design, material data, knowledge	Not available	[147]
		Multiphysics simulations	[148]
		Molecular dynamic, density functional theory simulations	[149]
	Smart electricity grid	Smart grid	[150]
		Smart electricity meters, cloud, artificial intelligence, IoT	[151]
	Consumer reviews, predictions	Not available	[152]
	Big Data transformation into value, BG system life cycle	Not available	[153], [154]

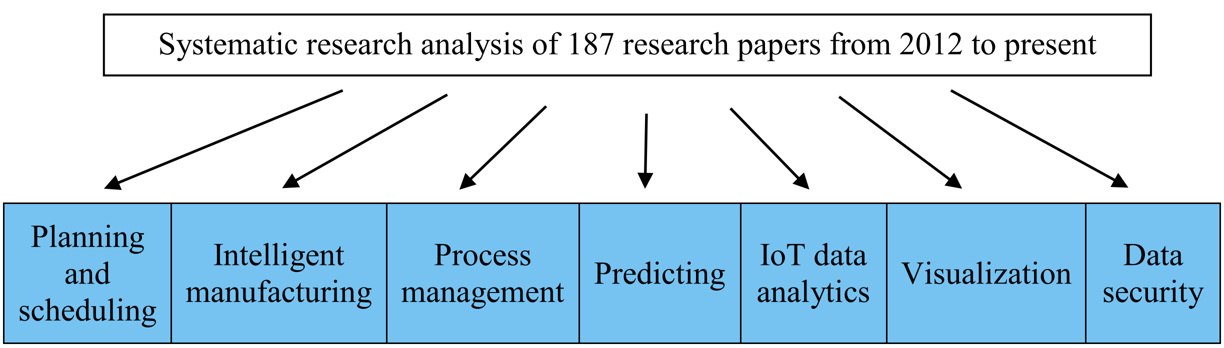

Fig. 4. Key BDA future research framework elements in IoT manufacturing (source: own).

(see above) depicts seven selected critical elements based on the previous analysis of the most cited research papers with a BD analytics search keyword.

The factors analyzed in the Industry 4.0 smart manufacturing category provide enough insight to define intelligent manufacturing, predicting, planning and scheduling, and process management as the BDA key elements in IoT intelligent manufacturing. The aspects such as real-time monitoring, autonomous management, decision-support making, and predictive analytics were also included. BI category factors (with the knowledge and decision-making focus) favored process management elements pursue as well. Technologies sensor-based data mining, 3V processing, parallel processing, and real-time analytics determine another factor that required further contemporary exploration within IoT data analytics. Visualization associated with managerial information in the Industry 4.0 category is also a useful topic in value creation. The general BD category also indicates the need for data security, decision-making support system, data analytics research, and efficient data processing, which correlated with the findings from the categories above (Industry 4.0, BI). The quality category did not return enough evidence to determine any element for further analysis.

After this extensive systematic analysis of the selected papers merged into four preliminary categories, the seven distinctive key elements were selected for the last research Stage 6.

Given this outcome, the contemporary academic literature was also analyzed (see Table VII below) to see possible future research fields regarding BDA in the context of Industry 4.0 implementation value creation.

The aim of this last research stage was to highlight major points that the authors identify to be an actual research gap. Following Fig. 4, selected research directions were classified

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TABLE VII
CHALLENGING RESEARCH DIRECTIONS OF BIG DATA ANALYTICS IN THE CONTEXT OF INDUSTRY 4.0 IN THE NEAR FUTURE (SOURCE: OWN)

Key elements	Research directions and general comments
Planning and scheduling	Enterprise resource planning is to be conducted in real time [60].
	Planning and innovating production management as the level of process automation increases [155].
	BDA-based demand planning, manufacturing, production and operation management [44].
	Knowledge-based scheduling decision-making model [156].
Intelligent manufacture	Data-driven manufacturing, RFID sensors in production, cloud technologies, human-machine collaboration [58], [59].
	Cyber-physical systems with BD algorithms [45], [157].
	Multisource heterogeneous big data processing and obtaining desired knowledge from vast amounts of data [41], [95].
	Creating efficient AI algorithms to retrieve real-time information using historical data to analyze information patterns [56].
	Complex event processing enables optimizing machine uptime and maintenance processes [158].
	Smart manufacturing and IT strategic management supported by Big Data Analytics [159].
Process management	Data-based decision-making utilization potential in process management [108], [160].
	Connection of productivity and analytics [31].
	Internal processes performance improving through BDA [7].
	Big Data affecting process and technology dimension of operations model in order to generate higher value [69].
	Improving firm agility with effective use of BDA tools [99].
	Conducting Big Data Analytics-driven project activities [161].
Predicting	Predicting future system behavior through, i.e., cloud computing [138].
	Prediction of production KPIs [162].
	Predictive informatics tools development to manage Big Data in IoT manufacturing [44].
	Establishing predictive maintenance model and multi-time-horizon predictions with regard to data security [163].
	Predicting work-in-progress model to optimize efficiency and reliability [156].
IoT data analytics	5G network to process vast data volumes effectively [23].
	Privacy, data mining, visualization, and integration [23].
	New methods, tools, and concepts; real-time system operations [164].
	Data organization, domain-oriented tools to create technologically advanced Big Data infrastructures [165].
	Data-driven decision-making Business Intelligence and Analytics (BI&A) and Big Data to create competitive advantages and business value in IoT manufacturing [11].
	Production capacity increase by means of collecting the transforming Big Data [15].
Visualization	Capturing all the value from the data in highly distinguished volumes of data [17].
	Virtualization of a cyber-physical system in production processes [166].
	Pre-processing and smoothing data for valid visual data interpretation [167].
Data security	Identifying data that contribute to the value creation and assess IT security risks [30].
	Improving security and reliability of the data in cyber-physical systems [168], [169].
	IoT devices as security platform in a manufacturing process [170].

into seven categories, respectively strategic key elements mentioned above.

V. DISCUSSION, LIMITATIONS, AND IMPLICATIONS

Based on the literature review and the systematic comprehensive research study and results achieved, BDA appears a critical driving force of value creation in various sectors, including IoT smart manufacturing. Due to the high complexity of the research problem and pursuing the main goal and research questions and hypotheses, we have provided, unlike many previous research studies, a more holistic and systematical view on the current and future trends in this area. Most previous research studies have addressed only a partial problem in this area, and therefore, we discuss achieved results gradually.

Original definitions of BD incorporate volume, variety, and velocity [86]. Some authors define more attributes regarding BD with another Vs as Valence, Variability, Value, and Veracity [2], [27], [41], or complexity [26], which we consider essential to manage smart manufacturing challenges. Based on our research results, we are consistent with the claim of Roberts and Laramee [17] that extracting value from BD will need to be a subject of future research. We find it essential to utilize the IoT to acquire data value because only this type of data is vital for sophisticated analytics in the prediction systems (see Figs. 4 and 5).

Some previous studies underscore manufacturing performance and the connection of BDA and strategic business decision-making [3], [11], [56], [57]. As we identified in Fig. 5, there are not only IT and analytics capabilities contributing to the increased performance, but one should not omit the process organization (identifying KPIs, logistics and production scheduling, strategic goals definition, and process optimization efforts). This is consistent with Wang *et al.* [162] that future researches will need to be concerned with complex production KPIs prediction algorithms. Moreover, and beyond the scope of our research study according to Oztemel and Gursev [59], or Horváth and Szabó [68], we need to note that Industry 4.0, together with the leading role of BI, is not only a technological step forward but also has a behavioral impact on managers and society.

In the context of research results achieved, we agree with Seddon *et al.* [4], Al-Fuqaha *et al.* [9], and Phillips-Wren *et al.* [11] that within IoT, many implications for managers arise. One of those might be that data-driven decision-making BI&A and BD can create competitive advantages for an organization by obtaining knowledge [4], [9], [11]. However, according to the latest current research published by Phillips-Wren *et al.* [11] in the journal decision support systems (July, 2021), this requires further research into the nature of organizational decision-making processes from BI&A and BD business value perspectives. We are pleased to find that the results of our research realized mostly during the year 2020 are well interconnected to this oncoming research. Also, according to Duan *et al.* [37], Oztemel

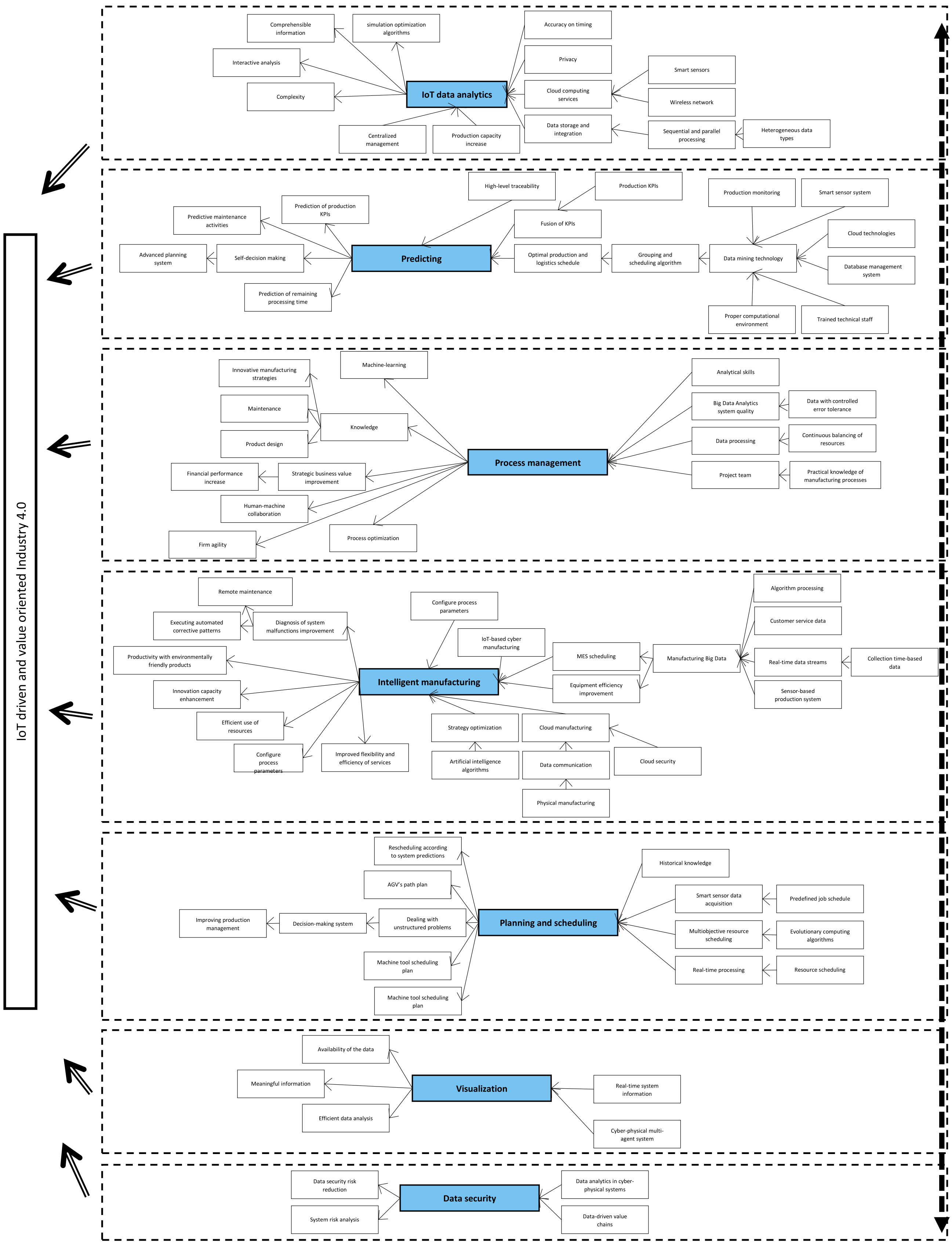

Fig. 5. IoT key elements for future research framework as a value creation gap (source: own).

and Gursev [59], and Zhong *et al.* [58], BD algorithms contribute to gaining knowledge which also corresponds with own findings.

The IoT has been a subject of many researches in the past years [9], [27], [28], [34], [35], [40], [76], [78] and this relevant topic pose many challenges nowadays, such as new concepts of real-time operation, efficient utilization of data, and production increase with BDA [2], [3], [15], [23], [46], [57], [69], [164], [171]. Moreover, based on our research results, we suggest once the BDA is fully implemented and optimized, benefits such as the production capacity increase, process predictions, knowledge obtaining, production flexibility increase, and scheduling system may be obtained (see research findings displayed in Figs. 4 and 5).

Our article results also answered the three partial research questions by confirming all research hypotheses set before in Section II:

> *H1:* BDA presents a highly important and discussed research topic. The article results confirmed that BDA is most frequently used in connection to general BD topics, services, and also the Industry 4.0 concept including smart manufacturing (see also Table I, Fig. 3).
>
> *H2:* In these four most discussed selected research areas (categories), we identified common factors such as research topics, technologies, and managerial tools directly related to BDA as the key elements of the business value creation (see Tables III–VI).
>
> *H3:* These identified key elements and methodological approach allowed us to find the strategic key elements in value creation within IoT intelligent manufacturing.

These article findings (see also Fig. 4, Table VII) allow us to define seven strategic elements—data analytics, predicting, process management, intelligent manufacturing, planning and scheduling, visualization, and data security as the key driving forces of business value creation within IoT smart manufacturing. This also concerns their future research framework (see Fig. 5 above). It complies partially with Qin [108], Liu *et al.* [160] that BDA is becoming a tremendous tool with decision-making in the context of the IoT intelligent manufacturing future research issue. Our research results are also in accordance with Phillips-Wren *et al.* [11] that data-driven decision-making BI&A and BD can create competitive advantages and higher business value in IoT manufacturing identifying as a new research opportunity. However, our findings are not consistent with the results of a systematic literature review provided by Ardito *et al.* [1], Saggi and Jain [2], Sheng *et al.* [3], Barlette and Baillette [6], Günther *et al.* [63], Mikalef *et al.* [64], as well as a descriptive qualitative studies conducted by Zhou *et al.* [66], Tao *et al.* [67], Horváth and Szabó [68], considering different factors to be crucial within this topic in future research.

Therefore, we can provide a key theoretical and practical implication that BDA within IoT in our comprehensive research study revealed to be overwhelmingly connected with both production and strategic processes in the company in the context of higher business value creation. *Process management* and *process optimization* have inevitably become a driver in managing the vast area of operating with and interpreting collected data. The IoT is a bridge between physical manufacturing and immaterial information flow. It is an essential asset to reach the *BI* level mediated by smart manufacturing. *Planning* and *scheduling*, *data prediction*, and *visualization* are closely related to the real-time data analytics in current production systems in order to pursue knowledge and business value creation following the vision of intelligent manufacturing, including also *data security* issue (see Fig. 5 , e.g., also Fig. 4 above).

Regarding the limitations of this article, we believe that our research findings are valid; however, the results may not be comprehensive and representative in terms of such a broad term "Internet of Things." The results also do not consider applications in other branches as services, healthcare, civil engineering, etc. Another limitation is the focus only on the Web of Science and Scopus database. Research results are partially also limited by using citation as only one search filter criterion (only papers with more than 100 citations were used).

On the other side, we can also propose some implications to future research. The results might be confronted with the findings achieved in future research papers worldwide. Unlike our holistic research approach based on a comprehensive systematic literature research study in possible future research, other different methodological approaches for example, a questionnaire survey in the practice can be used to compare with our research results achieved. It could also be interesting to examine this issue in other sectors such as services, healthcare, or even link our research scope to the behavioral aspects of this complex research problem.

VI. Conclusion

This article provides a comprehensive and holistic research study, uncovering relations between BDA and IoT key components, and at the same time finds a research gap in terms of Industry 4.0 and usage of BDA in the context of value creation within IoT intelligent manufacturing.

From the results, it can be concluded that BDA has become a stable topic in terms of usage starting in 2014. Out of overall results, the 187 articles (from the WoS and Scopus database) incorporating selected Industry 4.0 fields have slightly decreased over the last four years. However, these topics can still be considered very frequently used areas of research.

According to many previous research studies provided in the last decade, the BDA plays a significant and stable role within IoT and real-time-related technologies and approaches as cyber-physical systems, automated real-time data monitoring and processing, 5G network to manage data with vast volumes, variety, and velocity, or optimization through modeling in managing processes in companies within the Industry 4.0 concept.

Also, in the current academic research papers (see Table VII), the findings show potential directions of the IoT and BDA information support concerning Industry 4.0 manufacturing. One of the most important research directions is processing vast amounts of heterogeneous data alongside desirable network attributes and visualization. Another essential point is the utilization of the collected and processed data in large innovation capacity, autonomous production rescheduling, autonomous maintenance, smart manufacturing strategies, business planning, and predicting future outcomes of the managerial decisions.

However, our key research findings display that BDA and knowledge information support type BI are also imperative in value creation in Industry 4.0. The main state-of-the-art fields, whose context Industry 4.0 is researched and will need to be further exploited, are according to our results, these seven strategic key elements as driving forces to higher value creation within IoT intelligent manufacturing, namely *data analytics, predicting, process management, intelligent manufacturing, planning and scheduling, visualization, and data security*.

It is these seven strategic key elements and their connection to the application of recent technologies and methods in IoT manufacturing identified in the final research outcome (see Fig. 5), which can lead to higher *stability, productivity*, and *growth* to create higher *business value* and *competitiveness advantage*. This fundamental research finding is precisely what makes Fig. 1 shown in the introductory part of the article more dynamic and applicable in further research as well as in practice.

We dare to provide this final statement on the basis of our sufficient evidence presented in the article, when, unlike other previous studies [66], [68], we applied a systematic and relatively holistic research approach to solve this quite a complex research problem. This is also in line with the theory of strategic management and the theory of systems in general, whose primary task is to define crucial elements in a complex system based on a comprehensive analysis using a holistic approach.

Based on the presented above, we can conclude this article with the final suggestion in the form of the main strategic future research chain: *from IoT– through Big Data Analytics– to value creation based on Big Data Intelligence within IoT manufacturing*, whereas seven abovementioned strategic elements might play the crucial role in higher value creation within IoT intelligent manufacturing.

References

[1] L. Ardito, V. Scuotto, M. Del Giudice, and A. M. Petruzzelli, “A bibliometric analysis of research on big data analytics for business and management,” *Manage. Decis.*, vol. 57, no. 8, pp. 1993–2009, 2019.

[2] M. K. Saggi and S. Jain, “A survey towards an integration of big data analytics to big insights for value-creation,” *Inf. Process. Manage.*, vol. 54, no. 5, pp. 758–790, 2018.

[3] J. Sheng, J. Amankwah-Amoah, and X. Wang, “A multidisciplinary perspective of big data in management research,” *Int. J. Prod. Econ.*, vol. 191, pp. 97–112, 2017.

[4] P. B. Seddon, D. Constantinidis, T. Tamm, and H. Dod, “How does business analytics contribute to business value?,” *Inf. Syst. J.*, vol. 27, no. 3, pp. 237–269, 2017.

[5] L. Duan and L. D. Xu, “Data analytics in Industry 4.0: A survey,” *Inf. Syst. Frontier*, pp. 1–17, 2021. [Online]. Available: https://link.springer.com/content/pdf/10.1007/s10796-021-10190-0.pdf

[6] Y. Barlette and P. Baillette, “Big data analytics in turbulent contexts: Towards organizational change for enhanced agility,” *Prod. Planning Control*, pp. 1–18, 2020. [Online]. Available: https://www.tandfonline.com/doi/epub/10.1080/09537287.2020.1810755?needAccess=true

[7] M. Wiech, A. Boffelli, C. Elbe, P. Carminati, T. Friedli, and M. Kalchschmidt, “Implementation of big data analytics and manufacturing execution systems: An empirical analysis in German-speaking countries,” *Prod. Planning Control*, pp. 1–16, 2020. [Online]. Available: https://www.tandfonline.com/doi/epub/10.1080/09537287.2020.1810766?needAccess=true

[8] D. R. Sjödin, V. Parida, M. Leksell, and A. Petrovič, “Smart factory implementation and process innovation,” *Res.-Technol. Manage.*, vol. 61, no. 5, pp. 22–31, 2018.

[9] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of Things: A survey on enabling technologies, protocols, and applications,” *IEEE Commun. Surv. Tut.*, vol. 17, no. 4, pp. 2347–2376, Oct.–Dec. 2015.

[10] J. Jaklič, T. Grublješič, and A. Popovič, “The role of compatibility in predicting business intelligence and analytics use intentions,” *Int. J. Inf. Manage.*, vol. 43, pp. 305–318, 2018.

[11] G. Phillips-Wren, M. Daly, and F. Burstein, “Reconciling business intelligence, analytics and decision support systems: More data, deeper insight,” *Decis. Support Syst.*, vol. 146, 2021, Art. no. 113560.

[12] M. M. de Medeiros and A. C. G. Maçada, “Competitive advantage of data-driven analytical capabilities: The role of big data visualization and of organizational agility,” *Manage. Decis.*, to be published. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/MD-12-2020-1681/full/pdf?title=competitive-advantage-of-data-driven-analytical-capabilities-the-role-of-big-data-visualization-and-of-organizational-agility

[13] J. Ranjan and C. Foropon, “Big data analytics in building the competitive intelligence of organizations,” *Int. J. Inf. Manage.*, vol. 56, 2021, Art. no. 102231.

[14] U. Thirathon, B. Wieder, Z. Matolcsy, and M. L. Ossimitz, “Big data, analytic culture and analytic-based decision making evidence from Australia,” *Procedia Comput. Sci.*, vol. 121, pp. 775–783, 2017.

[15] J. Astill, R. A. Dara, E. D. G. Fraser, B. Roberts, and S. Sharif, “Smart poultry management: Smart sensors, big data, and the internet of things,” *Comput. Electron. Agriculture*, vol. 170, 2020, Art. no. 105291.

[16] S. F. Wamba, A. Gunasekaran, S. Akter, S. J. Ren, R. Dubey, and S. J. Childe, “Big data analytics and firm performance: Effects of dynamic capabilities,” *J. Bus. Res.*, vol. 70, pp. 356–365, 2017.

[17] R. Roberts and R. Laramee, “Visualising business data: A survey,” *Information*, vol. 9, no. 11, 2018, Art. no. 285.

[18] C. M. Olszak and J. Zurada, “Big data in capturing business value,” *Inf. Syst. Manage.*, vol. 37, no. 3, pp. 240–254, 2019.

[19] L. Furtado, M. Dutra, and D. Macedo, “Value creation in big data scenarios: A literature survey,” *J. Ind. Integr. Manage.*, vol. 2, no. 1, 2017, Art. no. 1750002.

[20] A. Popovič, R. Hackney, R. Tassabehji, and M. Castelli, “The impact of big data analytics on firms’ high value business performance,” *Inf. Syst. Frontier*, vol. 20, no. 2, pp. 209–222, 2018.

[21] F. E. Bordeleau, E. Mosconi, and L. A. De Santa-Eulalia, “Business intelligence and analytics value creation in Industry 4.0: A multiple case study in manufacturing medium enterprises,” *Prod. Planning Control*, vol. 31, no. 2–3, pp. 173–185, 2020.

[22] P. Xu, H. Mei, L. Ren, and W. Chen, “ViDX: Visual diagnostics of assembly line performance in smart factories,” *IEEE Trans. Vis. Comput. Graph.*, vol. 23, no. 1, pp. 291–300, Jan. 2017.

[23] M. Marjani *et al.*, “Big IoT data analytics: Architecture, opportunities, and open research challenges,” *IEEE Access*, vol. 5, pp. 5247–5261, 2017.

[24] O. Marjanovic, “A novel mechanism for business analytics value creation: Improvement of knowledge-intensive business processes,” *J. Knowl. Manage.*, to be published. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/JKM-09-2020-0669/full/pdf?title=a-novel-mechanism-for-business-analytics-value-creation-improvement-of-knowledge-intensive-business-processes

[25] A. De Mauro, M. Greco, and M. Grimaldi, “Understanding big data through a systematic literature review: The ITMI model,” *Int. J. Inf. Technol. Decis. Making*, vol. 18, no. 4, pp. 1433–1461, 2019.

[26] N. Khan *et al.*, “Big data: Survey, technologies, opportunities, and challenges,” *Sci. World J.*, vol. 2014, 2014, Art. no. 712826.

[27] C. Liu, C. Yang, X. Zhang, and J. Chen, “External integrity verification for outsourced big data in cloud and IoT: A big picture,” *Future Gener. Comput. Syst.*, vol. 49, pp. 58–67, 2015.

[28] S. Wang, J. Wan, D. Li, and C. Zhang, “Implementing smart factory of Industries 4.0: An outlook,” *Int. J. Distrib. Sensor Netw.*, vol. 12, no. 1, 2016, Art. no. 3159805.

[29] R. Agarwal and V. Dhar, “Big data, data science, and analytics: The opportunity and challenge for IS research,” *Inf. Syst. Res.*, vol. 25, no. 3, pp. 443–448, 2014.

[30] L. Bitomsky, O. Bürger, B. Häckel, and J. Töppel, “Value of data meets IT security-assessing IT security risks in data-driven value chains,” *Electron. Markets*, vol. 30, no. 3, pp. 589–605, 2020.

[31] S. J. Ren, S. F. Wamba, S. Akter, R. Dubey, and S. J. Childe, “Modelling quality dynamics, business value and firm performance in a big data analytics environment,” *Int. J. Prod. Res.*, vol. 55, no. 17, pp. 5011–5026, 2016.

[32] S. Sagiroglu and D. Sinanc, “Big data: A review,” in *Proc. Int. Conf. Collaboration Technol. Syst.*, 2013, pp. 42–47.

[33] Z. Sun, K. Strang, and S. Firmin, “Business analytics-based enterprise information systems,” *J. Comput. Inf. Syst.*, vol. 57, no. 2, pp. 169–178, 2016.

[34] M. Díaz, C. Martín, and B. Rubio, "State-of-the-art, challenges, and open issues in the integration of Internet of Things and cloud computing," *J. Netw. Comput. Appl.*, vol. 67, pp. 99–117, 2016.

[35] M. D. Assunção, R. N. Calheiros, S. Bianchi, M. A. S. Netto, and R. Buyya, "Big data computing and clouds: Trends and future directions," *J. Parallel Distrib. Comput.*, vol. 79–80, pp. 3–15, 2015.

[36] J. Li, F. Tao, Y. Cheng, and L. Zhao, "Big data in product lifecycle management," *Int. J. Adv. Manuf. Technol.*, vol. 81, no. 1–4, pp. 667–684, 2015.

[37] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of big data—Evolution, challenges and research agenda," *Int. J. Inf. Manage.*, vol. 48, pp. 63–71, 2019.

[38] M. Ghasemaghaei, S. Ebrahimi, and K. Hassanein, "Data analytics competency for improving firm decision making performance," *J. Strategic Inf. Syst.*, vol. 27, no. 1, pp. 101–113, 2018.

[39] H. Demirkan and D. Delen, "Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud," *Decis. Support Syst.*, vol. 55, no. 1, pp. 412–421, 2013.

[40] L. D. Xu, W. He, and S. Li, "Internet of Things in industries: A survey," *IEEE Trans. Ind. Inform.*, vol. 10, no. 4, pp. 2233–2243, Nov. 2014.

[41] S. Yin and O. Kaynak, "Big data for modern industry: Challenges and trends," *Proc. IEEE*, vol. 103, no. 2, pp. 143–146, Feb. 2015.

[42] E. Zeydan *et al.*, "Big data caching for networking: Moving from cloud to edge," *IEEE Commun. Mag.*, vol. 54, no. 9, pp. 36–42, Sep. 2016.

[43] P. Zheng *et al.*, "Smart manufacturing systems for industry 4.0: Conceptual framework, scenarios, and future perspectives," *Frontiers Mech. Eng.*, vol. 13, no. 2, pp. 137–150, 2018.

[44] Q. Feng and J. G. Shanthikumar, "How research in production and operations management may evolve in the era of big data," *Prod. Oper. Manage.*, vol. 27, no. 9, pp. 1670–1684, 2018.

[45] R. F. Babiceanu and R. Seker, "Big data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook," *Comput. Ind.*, vol. 81, pp. 128–137, 2016.

[46] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, "Deep learning for smart manufacturing: Methods and applications," *J. Manuf. Syst.*, vol. 48, pp. 144–156, 2018.

[47] O. Azeroual, G. Saake, and E. Schallehn, "Analyzing data quality issues in research information systems via data profiling," *Int. J. Inf. Manage.*, vol. 41, pp. 50–56, 2018.

[48] E. Siow, T. Tiropanis, and W. Hall, "Analytics for the internet of things: A survey," *ACM Comput. Surv.*, vol. 51, no. 4, 2018, Art. no. 74.

[49] D. Q. Chen, D. S. Preston, and M. Swink, "How the use of big data analytics affects value creation in supply chain management," *J. Manage. Inf. Syst.*, vol. 32, no. 4, pp. 4–39, 2015.

[50] R. Dubey, A. Gunasekaran, S. J. Childe, S. F. Wamba, and T. Papadopoulos, "The impact of big data on world-class sustainable manufacturing," *Int. J. Adv. Manuf. Technol.*, vol. 84, no. 1–4, pp. 631–645, 2016.

[51] G. Calic and M. Ghasemaghaei, "Big data for social benefits: Innovation as a mediator of the relationship between big data and corporate social performance," *J. Bus. Res.*, vol. 131, pp. 391–401, 2021.

[52] X. Yao, J. Zhou, Y. Lin, Y. Li, H. Yu, and Y. Liu, "Smart manufacturing based on cyber-physical systems and beyond," *J. Intell. Manuf.*, vol. 30, no. 8, pp. 2805–2817, 2019.

[53] K. Zhou, C. Fu, and S. Yang, "Big data driven smart energy management: From big data to big insights," *Renewable Sustain. Energy Rev.*, vol. 56, pp. 215–225, 2016.

[54] A. Alexandrov *et al.*, "The stratosphere platform for big data analytics," *VLDB J.*, vol. 23, no. 6, pp. 939–964, 2014.

[55] R. Rajnoha and S. Lorincová, "Strategic management of business performance based on innovations and information support in specific conditions of Slovakia," *J. Competitiveness*, vol. 7, no. 1, pp. 3–21, 2015.

[56] C. Liu, Y. Feng, D. Lin, L. Wu, and M. Guo, "IoT based laundry services: An application of big data analytics, intelligent logistics management, and machine learning techniques," *Int. J. Prod. Res.*, vol. 58, no. 17, pp. 5113–5131, 2020.

[57] Z. Lv, H. Song, P. Basanta-Val, A. Steed, and M. Jo, "Next-generation big data analytics: State of the art, challenges, and future research topics," *IEEE Trans. Ind. Inform.*, vol. 13, no. 4, pp. 1891–1899, 2017.

[58] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, "Intelligent manufacturing in the context of industry 4.0: A review," *Engineering*, vol. 3, no. 5, pp. 616–630, 2017.

[59] E. Oztemel and S. Gursev, "Literature review of industry 4.0 and related technologies," *J. Intell. Manuf.*, vol. 31, no. 1, pp. 127–182, 2020.

[60] H. Z., X. F. Zhan, Y. J. G. Liu, J. Zhang, H. S. H. Chung, and Y. Li, "Cloud computing resource scheduling and a survey of its evolutionary approaches," *ACM Comput. Surv.*, vol. 47, no. 4, pp. 1–33, 2015.

[61] H. S. Kang *et al.*, "Smart manufacturing: Past research, present findings, and future directions," *Int. J. Precis. Eng. Manuf.-Green Technol.*, vol. 3, no. 1, pp. 111–128, 2016.

[62] T. Poleto, V. D. H. De Carvalho, and A. P. C. S. Costa, "The full knowledge of big data in the integration of inter-organizational information," *Int. J. Decis. Support Syst. Technol.*, vol. 9, no. 1, pp. 16–31, 2017.

[63] W. A. Günther, M. H. Rezazade Mehrizi, M. Huysman, and F. Feldberg, "Debating big data: A literature review on realizing value from big data," *J. Strategic Inf. Syst.*, vol. 26, no. 3, pp. 191–209, 2017.

[64] P. Mikalef, I. O. Pappas, J. Krogstie, and M. Giannakos, "Big data analytics capabilities: A systematic literature review and research agenda," *Inf. Syst. e-Bus. Manage.*, vol. 16, no. 3, pp. 547–578, 2018.

[65] R. Alizadeh, P. D. Lund, and L. Soltanisehat, "Outlook on biofuels in future studies: A systematic literature review," *Renewable Sustain. Energy Rev.*, vol. 134, 2020, Art. no. 110326.

[66] K. Zhou, T. Liu, and L. Zhou, "Industry 4.0: Towards future industrial opportunities and challenges," in *Proc. 12th Int. Conf. Fuzzy Syst. Knowl. Discov.*, 2015, pp. 2147–2152.

[67] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," *J. Manuf. Syst.*, vol. 48, pp. 157–169, 2018.

[68] D. Horváth and R. Z. Szabó, "Driving forces and barriers of industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?," *Technol. Forecasting Social Change*, vol. 146, pp. 119–132, 2019.

[69] S. Roden, A. Nucciarelli, F. Li, and G. Graham, "Big data and the transformation of operations models: A framework and a new research agenda," *Prod. Planning Control*, vol. 28, no. 11–12, pp. 929–944, 2017.

[70] R. Alizadeh, R. G. Beiragh, L. Soltanisehat, E. Soltanzadeh, and P. D. Lund, "Performance evaluation of complex electricity generation systems: A dynamic network-based data envelopment analysis approach," *Energy Econ.*, vol. 91, 2020, Art. no. 104894.

[71] D. Tranfield, D. Denyer, and P. Smart, "Towards a methodology for developing evidence-informed management knowledge by means of systematic review," *Brit. J. Manage.*, vol. 14, no. 3, pp. 207–222, 2003.

[72] N. Becheikh, R. Landry, and N. Amara, "Lessons from innovation empirical studies in the manufacturing sector: A systematic review of the literature from 1993–2003," *Technovation*, vol. 26, no. 5–6, pp. 644–664, 2006.

[73] A. Booth, D. Papaloannou, and A. Sutton, *Systematic Approaches to a Successful Literature Review*. London, U.K.: Sage Publications, 2012.

[74] T. Hong, Z. Wang, X. Luo, and W. Zhang, "State-of-the-art on research and applications of machine learning in the building life cycle," *Energy Buildings*, vol. 212, no. 1, 2020, Art. no. 109831.

[75] F. Juliani and O. J. De Oliveira, "State of research on public service management: Identifying scientific gaps from a bibliometric study," *Int. J. Inf. Manage.*, vol. 36, no. 6, pp. 1033–1041, 2016.

[76] Y. Simmhan *et al.*, "Cloud-based software platform for big data analytics in smart grids," *Comput. Sci. Eng.*, vol. 15, no. 4, pp. 38–47, 2013.

[77] R. Y. Zhong, C. Xu, C. Chen, and G. Q. Huang, "Big data analytics for physical Internet-based intelligent manufacturing shop floors," *Int. J. Prod. Res.*, vol. 55, no. 9, pp. 2610–2621, 2017.

[78] R. Y. Zhong, S. Lan, C. Xu, Q. Dai, and G. Q. Huang, "Visualization of RFID-enabled shopfloor logistics big data in cloud manufacturing," *Int. J. Adv. Manuf. Technol.*, vol. 84, no. 1–4, pp. 5–16, 2016.

[79] H. El-Sayed *et al.*, "Edge of things: The big picture on the integration of edge, IoT and the cloud in a distributed computing environment," *IEEE Access*, vol. 6, pp. 1706–1717, 2018.

[80] J. Dittrich and J. A. Quiané-Ruiz, "Efficient big data processing in hadoop mapreduce," *Proc. VLDB Endowment*, vol. 5, no. 12, pp. 2014–2015, 2012.

[81] J. Xu, E. Huang, C. H. Chen, and L. H. Lee, "Simulation optimization: A review and exploration in the new era of cloud computing and big data," *Asia-Pacific J. Oper. Res.*, vol. 32, no. 3, 2015, Art. no. 1550019.

[82] M. H. ur, V. C. Rehman, A. Batool, and T. Y. Wah, "Big data reduction framework for value creation in sustainable enterprises," *Int. J. Inf. Manage.*, vol. 36, no. 6, pp. 917–928, 2016.

[83] J. Lee, E. Lapira, B. Bagheri, and H. Kao, "Recent advances and trends in predictive manufacturing systems in big data environment," *Manuf. Lett.*, vol. 1, no. 1, pp. 38–41, 2013.

[84] R. Ranjan, "Streaming big data processing in datacenter clouds," *IEEE Cloud Comput.*, vol. 1, no. 1, pp. 78–83, May 2014.

[85] D. A. Reed and J. Dongarra, "Exascale computing and big data," *Commun. ACM*, vol. 58, no. 7, pp. 56–68, 2015.

[86] R. Lu, H. Zhu, X. Liu, J. K. Liu, and J. Shao, "Toward efficient and privacy-preserving computing in big data era," *IEEE Netw.*, vol. 28, no. 4, pp. 46–50, Jul./Aug. 2014.

[87] T. M. Choi, S. W. Wallace, and Y. Wang, "Big data analytics in operations management," *Prod. Oper. Manage.*, vol. 27, no. 10, pp. 1868–1883, 2018.

[88] H. Zhang, G. Chen, B. C. Ooi, K. L. Tan, and M. Zhang, "In-memory big data management and processing: A survey," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 7, pp. 1920–1948, Jul. 2015.

[89] A. Imran and A. Zoha, "Challenges in 5G: How to empower SON with big data for enabling 5G," *IEEE Netw.*, vol. 28, no. 6, pp. 27–33, Nov./Dec. 2014.

[90] K. Zheng, Z. Yang, K. Zhang, P. Chatzimisios, K. Yang, and W. Xiang, "Big data-driven optimization for mobile networks toward 5G," *IEEE Netw.*, vol. 30, no. 1, pp. 44–51, Jan./Feb. 2016.

[91] Y. Zhai, Y. S. Ong, and I. W. Tsang, "The emerging 'Big dimensionality'," *IEEE Comput. Intell. Mag.*, vol. 9, no. 3, pp. 14–26, Nov./Dec. 2014.

[92] A. L'Heureux, K. Grolinger, H. F. Elyamany, and M. A. M. Capretz, "Machine learning with big data: Challenges and approaches," *IEEE Access*, vol. 5, pp. 7776–7797, 2017.

[93] M. Mohammadi, A. Al-Fuqaha, S. Sorour, and M. Guizani, "Deep learning for IoT big data and streaming analytics: A survey," *IEEE Commun. Surv. Tut.*, vol. 20, no. 4, pp. 2923–2960, Oct.–Dec. 2018.

[94] Y. Wang, Q. Chen, T. Hong, and C. Kang, "Review of smart meter data analytics: Applications, methodologies, and challenges," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3125–3148, May 2019.

[95] Y. Zhang, S. Ren, Y. Liu, and S. Si, "A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products," *J. Cleaner Prod.*, vol. 142, pp. 626–641, 2017.

[96] R. Roy, R. Stark, K. Tracht, S. Takata, and M. Mori, "Continuous maintenance and the future—Foundations and technological challenges," *CIRP Ann.-Manuf. Technol.*, vol. 65, no. 2, pp. 667–688, 2016.

[97] A. G. Frank, L. S. Dalenogare, and N. F. Ayala, "Industry 4.0 technologies: Implementation patterns in manufacturing companies," *Int. J. Prod. Econ.*, vol. 210, pp. 15–26, 2019.

[98] R. Strange and A. Zucchella, "Industry 4.0, global value chains and international business," *Multinational Bus. Rev.*, vol. 25, no. 3, pp. 174–184, 2017.

[99] M. Ghasemaghaei, K. Hassanein, and O. Turel, "Increasing firm agility through the use of data analytics: The role of fit," *Decis. Support Syst.*, vol. 101, pp. 95–105, 2017.

[100] K. Kambatla, G. Kollias, V. Kumar, and A. Grama, "Trends in big data analytics," *J. Parallel Distrib. Comput.*, vol. 74, no. 7, pp. 2561–2573, 2014.

[101] A. A. Cardenas, P. K. Manadhata, and S. P. Rajan, "Big data analytics for security," *IEEE Secur. Privacy*, vol. 11, no. 6, pp. 74–76, Nov./Dec. 2013.

[102] M. Andrejevic, "The big data divide," *Int. J. Commun.*, vol. 8, pp. 1673–1689, 2014.

[103] D. Barton and D. Court, "Making advanced analytics work for you," *Harvard Bus. Rev.*, vol. 90, no. 10, pp. 78–83, 2012.

[104] D. Fisher, R. DeLine, M. Czerwinski, and S. Drucker, "Interactions with big data analytics," *Interactions*, vol. 19, no. 3, pp. 50–59, 2012.

[105] C. Loebbecke and A. Picot, "Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda," *J. Strategic Inf. Syst.*, vol. 24, no. 3, pp. 149–157, 2015.

[106] J. M. Tien, "Big data: Unleashing information," *J. Syst. Sci. Syst. Eng.*, vol. 22, no. 2, pp. 127–151, 2013.

[107] J. Leskovec and R. Sosič, "SNAP: A general-purpose network analysis and graph-mining librar," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 1, pp. 1–20, 2016.

[108] S. J. Qin, "Process data analytics in the era of big data," *AICHE J.*, vol. 60, no. 9, pp. 3092–3100, 2014.

[109] U. Sivarajah, M. M. Kamal, Z. Irani, and V. Weerakkody, "Critical analysis of big data challenges and analytical methods," *J. Bus. Res.*, vol. 70, pp. 263–286, 2017.

[110] T. H. Davenport, "Analytics 3.0," *Harvard Bus. Rev.*, vol. 91, no. 12, pp. 64–72, 2013.

[111] M. A. Alsheikh, D. Niyato, S. Lin, H. Tan, and Z. Han, "Mobile big data analytics using deep learning and apache spark," *IEEE Netw.*, vol. 30, no. 3, pp. 22–29, May/Jun. 2016.

[112] X. W. Chen and X. Lin, "Big data deep learning: Challenges and perspectives," *IEEE Access*, vol. 2, pp. 514–525, 2014.

[113] M. M. Najafabadi, F. Villanustre, T. M. Khoshgoftaar, N. Seliya, R. Wald, and E. Muharemagic, "Deep learning applications and challenges in big data analytics," *J. Big Data*, vol. 2, no. 1, 2015, Art. no. 1.

[114] K. Slavakis, G. B. Giannakis, and G. Mateos, "Modeling and optimization for big data analytics," *IEEE Signal Process. Mag.*, vol. 31, no. 5, pp. 18–31, Sep. 2014.

[115] A. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," *Int. J. Inf. Manage.*, vol. 35, no. 2, pp. 137–144, 2015.

[116] D. Singh and C. K. Reddy, "A survey on platforms for big data analytics," *J. Big Data*, vol. 2, no. 1, 2015, Art. no. 8.

[117] K. Singh, S. C. Guntuku, A. Thakur, and C. Hota, "Big data analytics framework for peer-to-peer botnet detection using random forests," *Inf. Sci.*, vol. 278, pp. 488–497, 2014.

[118] J. Wang, P. Zhao, S. C. H. Hoi, and R. Jin, "Online feature selection and its applications," *IEEE Trans. Knowl. Data Eng.*, vol. 26, no. 3, pp. 698–710, Mar. 2014.

[119] E. Ahmed *et al.*, "The role of big data analytics in Internet of Things," *Comput. Netw.*, vol. 129, pp. 459–471, 2017.

[120] I. D. Constantiou and J. Kallinikos, "New games, new rules: Big data and the changing context of strategy," *J. Inf. Technol.*, vol. 30, no. 1, pp. 44–57, 2015.

[121] M. Hilbert, "Big data for development: A review of promises and challenges," *Develop. Policy Rev.*, vol. 34, no. 1, pp. 135–174, 2016.

[122] M. Gupta and J. F. George, "Toward the development of a big data analytics capability," *Inf. Manage.*, vol. 53, no. 8, pp. 1049–1064, 2016.

[123] A. Gunasekaran *et al.*, "Big data and predictive analytics for supply chain and organizational performance," *J. Bus. Res.*, vol. 70, pp. 308–317, 2017.

[124] T. Papadopoulos, A. Gunasekaran, R. Dubey, N. Altay, S. J. Childe, and S. Fosso-Wamba, "The role of big data in explaining disaster resilience in supply chains for sustainability," *J. Cleaner Prod.*, vol. 142, pp. 1108–1118, 2017.

[125] C. W. Tsai, C. F. Lai, H. C. Chao, and A. V. Vasilakos, "Big data analytics: A survey," *J. Big Data*, vol. 2, no. 1, 2015, Art. no. 21.

[126] T. Rabl, S. Gómez-Villamor, M. Sadoghi, V. Muntés-Mulero, H. A. Jacobsen, and S. Mankovskii, "Solving big data challenges for enterprise application performance management," *Proc. VLDB Endowment*, vol. 5, no. 12, pp. 1724–1735, 2012.

[127] F. Bonomi, R. Milito, P. Natarajan, and J. Zhu, "Fog computing: A platform for internet of things and analytics," in *Big Data and Internet of Things: A Roadmap for Smart Environments*, N. Bessis and C. Dobre Eds. Cham, Switzerland: Springer International Publishing, 2014, pp. 169–186.

[128] V. Cevher, S. Becker, and M. Schmidt, "Convex optimization for big data: Scalable, randomized, and parallel algorithms for big data analytics," *IEEE Signal Process. Mag.*, vol. 31, no. 5, pp. 32–43, Sep. 2014.

[129] M. Satyanarayanan *et al.*, "Edge analytics in the internet of things," *IEEE Pervasive Comput.*, vol. 14, no. 2, pp. 24–31, Apr.–Jun. 2015.

[130] S. F. Wamba, S. Akter, A. Edwards, G. Chopin, and D. Gnanzou, "How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study," *Int. J. Prod. Econ.*, vol. 165, pp. 234–246, 2015.

[131] M. Janssen, H. Van der Voort, and A. Wahyudi, "Factors influencing big data decision-making quality," *J. Bus. Res.*, vol. 70, pp. 338–345, 2017.

[132] A. McAfee and E. Brynjolfsson, "Strategy and competition big data: The management revolution," *Harvard Bus. Rev.*, vol. 90, no. 10, pp. 60–68, 2012.

[133] H. J. Watson, "Tutorial: Big data analytics," *Commun. Assoc. Inf. Syst.*, vol. 34, 2014, Art. no. 65.

[134] D. Dutta and I. Bose, "Managing a big data project: The case of ramco cements limited," *Int. J. Prod. Econ.*, vol. 165, pp. 293–306, 2015.

[135] R. Sharma, S. Mithas, and A. Kankanhalli, "Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations," *Eur. J. Inf. Syst.*, vol. 23, no. 4, pp. 433–441, 2017.

[136] H. Chen, R. Chiang, and V. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Quart.*, vol. 36, no. 4, pp. 1165–1188, 2012.

[137] D. Talia, "Clouds for scalable big data analytics," *Computer*, vol. 46, no. 5, pp. 98–101, 2013.

[138] A. Fernández *et al.*, "Big data with cloud computing: An insight on the computing environment, mapreduce, and programming frameworks," *Wiley Interdisciplinary Rev.: Data Mining Knowl. Discov.*, vol. 4, no. 5, pp. 380–409, 2014.

[139] C. Doulkeridis and K. Nørvåg, "A survey of large-scale analytical query processing in mapreduce," *VLDB J.*, vol. 23, no. 3, pp. 355–380, 2014.

[140] H. Hu, Y. Wen, T. S. Chua, and X. Li, "Toward scalable systems for big data analytics: A technology tutorial," *IEEE Access*, vol. 2, pp. 652–687, 2014.

[141] B. Wixom *et al.*, "The current state of business intelligence in academia: The arrival of big data," *Commun. Assoc. Inf. Syst.*, vol. 34, pp. 1–13, 2014.
[142] S. Akter, S. F. Wamba, A. Gunasekaran, R. Dubey, and S. J. Childe, "How to improve firm performance using big data analytics capability and business strategy alignment?," *Int. J. Prod. Econ.*, vol. 182, pp. 113–131, 2016.
[143] D. Larson and V. Chang, "A review and future direction of agile, business intelligence, analytics and data science," *Int. J. Inf. Manage.*, vol. 36, no. 5, pp. 700–710, 2016.
[144] N. Côrte-Real, T. Oliveira, and P. Ruivo, "Assessing business value of big data analytics in European firms," *J. Bus. Res.*, vol. 70, pp. 379–390, 2017.
[145] R. Vidgen, S. Shaw, and D. B. Grant, "Management challenges in creating value from business analytics," *Eur. J. Oper. Res.*, vol. 261, no. 2, pp. 626–639, 2017.
[146] O. Kwon, N. Lee, and B. Shin, "Data quality management, data usage experience and acquisition intention of big data analytics," *Int. J. Inf. Manage.*, vol. 34, no. 3, pp. 387–394, 2014.
[147] S. V. Kalinin, B. G. Sumpter, and R. K. Archibald, "Big-deep-smart data in imaging for guiding materials design," *Nature Mater.*, vol. 14, no. 10, pp. 973–980, 2015.
[148] S. R. Kalidindi and M. De Graef, "Materials data science: Current status and future outlook," *Annu. Rev. Mater. Res.*, vol. 45, no. 1, pp. 171–193, 2015.
[149] A. Agrawal and A. Choudhary, "Perspective: Materials informatics and big data," *APL Mater.*, vol. 4, no. 5, 2016, Art. no. 053208.
[150] P. D. Diamantoulakis, V. M. Kapinas, and G. K. Karagiannidis, "Big data analytics for dynamic energy management in smart grids," *Big Data Res.*, vol. 2, no. 3, pp. 94–101, 2015.
[151] D. Alahakoon and X. Yu, "Smart electricity meter data intelligence for future energy systems: A survey," *IEEE Trans. Ind. Inform.*, vol. 12, no. 1, pp. 425–436, Feb. 2016.
[152] M. Salehan and D. J. Kim, "Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics," *Decis. Support Syst.*, vol. 81, pp. 30–40, 2016.
[153] J. Wu, S. Guo, J. Li, and D. Zeng, "Big data meet green challenges: Big data toward green applications," *IEEE Syst. J.*, vol. 10, no. 3, pp. 888–900, Sep. 2016.
[154] J. Wu, S. Guo, J. Li, and D. Zeng, "Big data meet green challenges: Greening big data," *IEEE Syst. J.*, vol. 10, no. 3, pp. 873–887, Sep. 2016.
[155] L. Mylnikov, "Management and information support issues in the implementation of innovation projects in production systems," in *Proc. 7th Int. Conf. Appl. Innov. IT*, 2019, pp. 55–63.
[156] G. Zhou, C. Zhang, Z. Li, K. Ding, and C. Wang, "Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing," *Int. J. Prod. Res.*, vol. 58, no. 4, pp. 1034–1051, 2020.
[157] T. Borangiu, O. Morariu, S. Raileanu, D. Trentesaux, P. Leitao, and J. Barata, "Digital transformation of manufacturing. Industry of the future with cyber-physical production systems," *Romanian J. Inf. Sci. Technol.*, vol. 23, no. 1, pp. 3–37, 2020.
[158] J. Wanner, C. Wissuchek, and C. Janiescha, "Machine learning and complex event processing a review of Real-time data analytics for the industrial internet of things," *Enterprise Model. Inf. Syst. Architectures–Int. J.*, vol. 15, no. 1, pp. 1–27, 2020.
[159] M. Ghobakhloo, "The future of manufacturing industry: A strategic roadmap toward industry 4.0.," *J. Manuf. Technol. Manage.*, vol. 29, no. 6, pp. 910–936, 2018.
[160] Y. Liu, Y. Zhang, S. Ren, M. Yang, Y. Wang, and D. Huisingh, "How can smart technologies contribute to sustainable product lifecycle management?," *J. Cleaner Prod.*, vol. 249, 2020, Art. no. 119423.
[161] D. Kozjek, R. Vrabič, B. Rihtaršič, N. Lavrač, and P. Butala, "Advancing manufacturing systems with big-data analytics: A conceptual framework," *Int. J. Comput. Integr. Manuf.*, vol. 33, no. 2, pp. 169–188, 2020.
[162] W. Wang, Y. Zhang, and R. Y. Zhong, "A proactive material handling method for CPS enabled shop-floor," *Robot. Comput.-Integr. Manuf.*, vol. 61, 2020, Art. no. 101849.
[163] S. Panicucci *et al.*, "A cloud-to-edge approach to support predictive analytics in robotics industry," *Electronics*, vol. 9, no. 3, 2020, Art. no. 492.
[164] H. P. Breivold, "Internet-of-Things and cloud computing for smart industry: A systematic mapping study," in *Proc. 5th Int. Conf. Enterprise Syst.*, 2017, pp. 299–304.
[165] A. Oussous, F. Z. Benjelloun, A. Ait Lahcen, and S. Belfkih, "Big data technologies: A survey," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 30, no. 4, pp. 431–448, 2018.
[166] Z. Huang, J. Kim, A. Sadri, S. Dowey, and M. S. Dargusch, "Industry 4.0: Development of a multi-agent system for dynamic value stream mapping in SMEs," *J. Manuf. Syst.*, vol. 52, pp. 1–12, 2019.
[167] T. J. Saleem and M. A. Chishti, "Data analytics in the internet of things: A survey," *Scalable Comput.: Pract. Experience*, vol. 20, no. 4, pp. 607–630, 2019.
[168] L. D. Xu and L. Duan, "Big data for cyber physical systems in Industry 4.0: A survey," *Enterprise Inf. Syst.*, vol. 13, no. 2, pp. 148–169, 2018.
[169] F. Zhou *et al.*, "A survey of visualization for smart manufacturing," *J. Vis.*, vol. 22, no. 2, pp. 419–435, 2019.
[170] M. Syafrudin, G. Alfian, N. Fitriyani, and J. Rhee, "Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing," *Sensors*, vol. 18, no. 9, 2018, Art. no. 2946.
[171] V. Grover, R. H. L. Chiang, T. P. Liang, and D. Zhang, "Creating strategic business value from big data analytics: A research framework," *J. Manage. Inf. Syst.*, vol. 35, no. 2, pp. 388–423, 2018.

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