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Review

# Big Data for Healthcare Industry 4.0: Applications, challenges and future perspectives

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ABSTRACT

The innovative technologies emerged with the industrial revolution “Industry 4.0" as well as the new ones on the way of advanced digitalization enable delivering enhanced, value-added and cost-effective manufacturing and service operations. One of the first areas of focus for Industry 4.0 applications is operations related to healthcare services. Effective management of healthcare resources, clinical care processes, service planning, delivery and evaluation of healthcare operations are essential for a well-functioning healthcare system. Yet, with the adoption of technologies such as Internet of Health Things, Medical Cyber–Physical Systems, Machine Learning, and Big Data (BD), the healthcare sector has recognized the relevance of Industry 4.0. The concept of BD offered numerous advantages and opportunities in this field. It changed the way information is gathered, shared and utilized. Hence, in this study our main ambition is to provide readers with a review of publications which lie within the intersection of Industry 4.0, BD, and healthcare operations and give future perspectives. Our review shows that BD constitutes an important place on the technologies Industry 4.0 provides in the healthcare domain. It helps design, improve, analyze, assess and optimize operations in the domain.

## 1. Introduction

Worldwide industrial growth started with the First Industrial Revolution in the 18th century. Industries are generally classified as primary (Industry 1.0), secondary (Industry 2.0), tertiary (Industry 3.0), and fourth (Industry 4.0) that started in the 21st century and is a new course in the technology races of countries. The first industrial revolution (1.0) emerged in the 1800s with mechanical production systems using water and steam power. With the second industrial revolution (2.0), which started the around 1870 and 1970 (Xu, Xu, & Li, 2018), mass production started with the help of electric power. The third industrial revolution started in the 1970s with partial automation using computers and the automation industries (Vinitha, Prabhu, Bhaskar, & Hariharan, 2020). With the use of electronics and the development of Information Technology (IT) in this industrial revolution, production has been further automated. The latest industrial revolution, Industry 4.0, aims to create fully autonomous machines and virtual environments by the implementation of multiple technologies. More importantly, Industry 4.0 attempts to integrate the philosophy of how these technologies are to be used both in manufacturing and service systems (Gunal & Karatas, 2019). The evolution of Industry 4.0 is illustrated in Fig. 1.

Industry 4.0 was introduced by Kagermann, Lukas, and Wahlster (2011) as a pioneer of smart manufacturing to maintain the future competitiveness of German industry. This concept has become a government policy in Germany. The technologies of Industry 4.0 attempted to integrate devices that can communicate autonomously between each other, have a decision-making mechanism, and even learn, both in production and life. It includes cyber–physical systems (CPS), internet of things (IoT), cyber security (CS), autonomous robots, cloud computing (CC), simulation, smart devices and BD (Akyurt, Kuvvetli, & Deveci, 2020). With the help of vertical, horizontal and end-to-end integration, Industry 4.0 is intended to change the face of the manufacturing industry, increase productivity and provide cost, time and energy saving (Raj, Dwivedi, Sharma, de Sousa Jabbour, & Rajak, 2020). Industry 4.0 helps virtualization and modularization of production processes by gaining flexibility based on CPS and IoT along with

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**Acronyms**

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **AR** | Augmented Reality |
| **BD** | Big Data |
| **BDE** | Big Data Exploration |
| **CHAID** | Chi-squared Automatic Interaction Detection |
| **CC** | Cloud Computing |
| **CPS** | Cyber Physical Systems |
| **DL** | Deep Learning |
| **DM** | Data Mining |
| **DSS** | Decision Support System |
| **ERP** | Enterprise Resource Planning |
| **FC** | Fog Computing |
| **HMS** | Health Monitoring Systems |
| **ICT** | Information and Communication Technologies |
| **IoHT** | Internet of Health Things |
| **IoMT** | Internet of Medical Things |
| **IoT** | Internet of Things |
| **LSTM** | Long Short Term Memory |
| **ML** | Machine Learning |
| **MCPS** | Medical Cyber–Physical Systems |
| **OSA** | Obtrusive Sleep Apnea |
| **RT** | Random Tree |
| **RFID** | Radio Frequency Identification |
| **SNA** | Social Network Analysis |
| **SHS** | Smart Hospital System |
| **SCM** | Supply Chain Management |
| **SVM** | Support Vector Machines |
| **TCM** | Traditional Chinese Medicine |
| **VAD** | Ventricular Assist Device |
| **VR** | Virtual Reality |
| **WHO** | World Health Organization |
| **WSN** | Wireless Sensor Network |

enterprise resource planning (ERP), supply chain management (SCM) and other systems (Chen & Xing, 2015).

One of the most important components of Industry 4.0 revolution is "Big Data". BD and Industry 4.0 are technologies related to CPS and CC, and mainly deal with sharing data with the entire value chain of the industry (Singh, 2020). Although the earlier definitions of the term "big data" focused on the size of the raw data, a complete definition should also account for the variety and velocity aspects, i.e. the 3Vs as volume, variety, and velocity, of the data (Russom et al., 2011). Hence, BD can be regarded as large volumes of complex, growing data sets obtained from multiple and heterogeneous autonomous resources (Wu, Zhu, Wu, & Ding, 2013). Consequently, the existence of massive amounts of data and the analytic approaches required to collect, analyze, store and predict data brought out the concept of BD analytics (Russom et al., 2011).

During the COVID-19 pandemic, which remains uncertain in many ways and continues to be intensely researched, the healthcare industry has begun to use data analytical methods to better understand the virus and its spread. Researchers and clinicians are rapidly seeking solutions in the fields of machine learning (ML), which is essentially a subset of artificial intelligence (AI) and corresponds to algorithms that can improve automatically through experience, and data science in their quest to better monitor and respond to the situation. Therefore, the spread of diseases, detection of risky areas, their follow-up and potential effects have been determined with the use of these techniques intensively in the health sector for the analysis of the resulting BD. It has helped track the virus in populations, even down to the neighborhood level. It has also been used in strategic planning and decision-making processes to anticipate and prepare for future pandemics. Various smart systems such as smart home and office have been developed to monitor the health status of workers, elderly and patients. At the same time, it is important to keep patients' data, networks and systems safe to ensure the uninterrupted operation of life-saving information and devices. Cybersecurity has become critical to the continued operation of healthcare services[1].

In recent years, BD plays a critical role in almost all application analysis, such as environmental monitoring, transportation (Alic, et al., 2019; Gohar, Muzammal, & Rahman, 2018; Ma & Chen, 2019), smart city (Chen, Ramanathan, & Alazab, 2021), education (Drayton-Brooks, Gray, Turner, & Newland, 2020; Hussein Ali, Faiz Hussain, & N. Abd, 2020; Pardos, 2017), manufacturing (Ma, et al., 2020; Majeed, et al., 2021; Zhang, Ming, & Yin, 2020), banking and security (Merhi, Hone, & Tarhini, 2019), insurance (Fang, Jiang, & Song, 2016; Koutsomitropoulos & Kalou, 2017), social media (Al-mashhadani, Hussein, Khudir, & Ilyas, 2022; Liu, Shin, & Burns, 2019; Pellakuri, Rao, Pellakuri, & Parveen, 2021), energy and efficiency (Haseeb, Lee, & Jeon, 2020), face intelligent and recognition (Lei, 2022; Yang & Xing, 2022), and healthcare applications (Karatas, Karacan, & Tozan, 2018; Manogaran, Thota, Lopez, & Sundarasekar, 2017). With the rapid increase in technological developments, the synergy between medicine and technology has increased and led to the development of new devices (Zhan, 2020). Patient's health prediction, diabetes diagnosis, sleep monitoring and sleep health, infectious diseases such as tuberculosis are studied by several researchers in the context of BD implementation and Industry 4.0 revolution. In particular, wearable medical devices with sensors collect rich information for our physical and mental health. With the rapid development of the IoT, it causes a large amount of data generated from wearable devices and sensors (Pham, Nguyen, Huynh-The, Hwang, & Pathirana, 2020). Enormous data called "Big Data" is constantly generated by these sensors. It is generally difficult to process and analyze BD to find valuable information. Therefore, an efficient and secure architecture are required for organizations to handle BD in integrated industry 4.0 (Manogaran et al., 2017).

A number of technologies provide benefits for the prevention or management of chronic diseases. These cover devices that continuously monitor health indicators, devices that automatically deliver treatments, or devices that monitor real-time health data when a patient self-administers a therapy. With increased access to high-speed internet and smart phones, many patients have started using mobile applications to manage their various health needs. These devices and mobile applications are now increasingly used in the healthcare field and are being integrated with telemedicine and telehealth via the medical Internet of Things (mIoT) (Dimitrov, 2016). In particular, IoT is widely performed to connect existing medical resources and provide reliable, effective and intelligent healthcare to the elderly and patients with a chronic diseases (Souza, da Costa, de Oliveira Ramos, & da Rosa Righi, 2020). IoT is redesigning modern healthcare services with promising technological, economic and social expectations (Islam, Kwak, Kabir, Hossain, & Kwak, 2015).

The main aim of this study is to present a comprehensive survey of studies which use BD technology for healthcare in the context of Industry 4.0. To achieve this, we used academic databases to track papers on BD for healthcare. The survey methodology used in this study is summarized in Section 2. In Section 3, we reviewed these articles to investigate their impact on healthcare services in terms of methodology

[1] https://www.elsevier.com/connect/ai-big-data-cybersecurity-and-iot-in-the-era-of-coronavirus

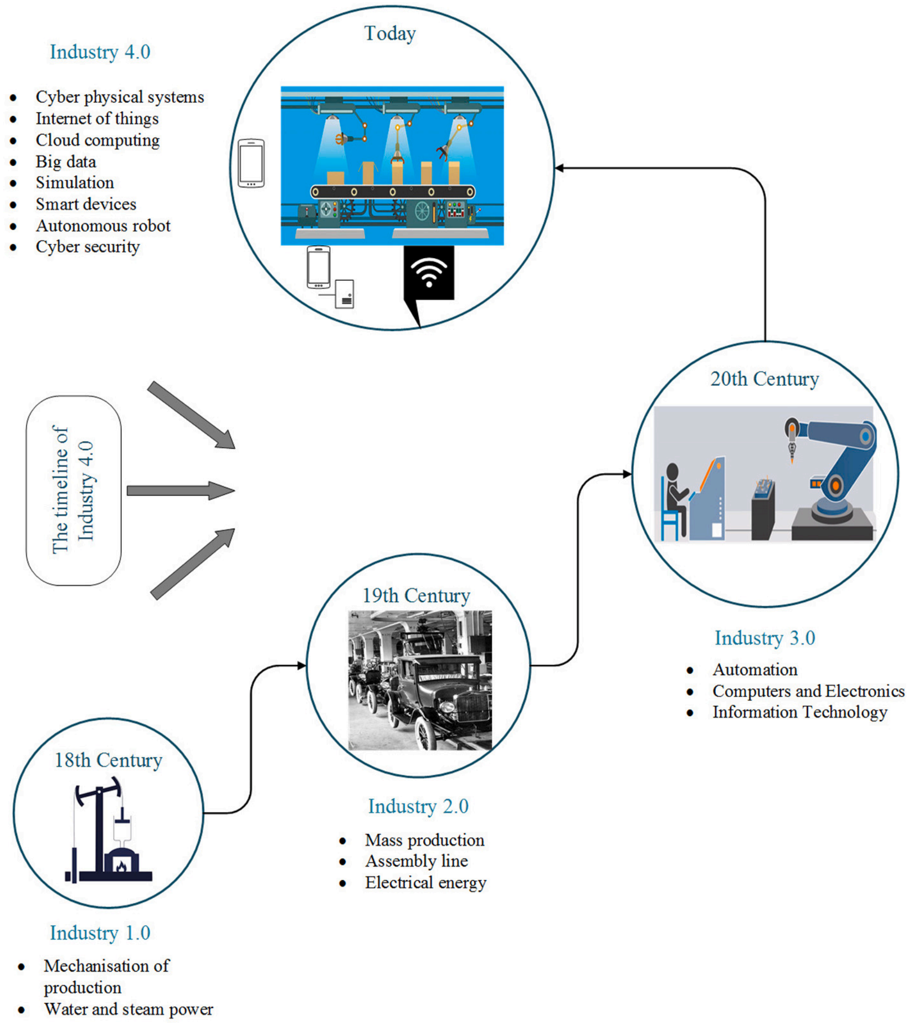


**Fig. 1.** The timeline of Industry 4.0.

and practice. While doing this we also examined the history and advancement of Industry 4.0 based technologies for medical applications. In particular, we consider BD related technologies in healthcare services from the perspectives of IoT, CS, CC, MCPS, data privacy & security, etc. In Section 4, we discuss the quantitative information regarding the studies included in our survey. We finally present the future trends and potential directions of research in Section 5.

## 2. Survey methodology

The concept of Industry 4.0 yielded a number of technological innovations such as IoT, CC, FG, AR, autonomous manufacturing systems, BD, horizontal and vertical system integration, cybersecurity, and simulation. Most of these technologies are still developing in both service and manufacturing systems (Gunal & Karatas, 2019). Over the last decade, the application and implementation of BD research has attracted attention among academicians and practitioners from various domains in the context of Industry 4.0. Among these domains, healthcare services are relatively more popular due to the huge improvement potential in healthcare related operations and services. BD-driven software and hardware implementations combined with technologies such as CC, FG, IoT and ML have proven to be efficient in terms of health management and other medical applications.

Hence, in our review, we mainly focus on journal papers, conference papers, and book chapters addressing the use of BD applications in Industry 4.0 domain with a focus on healthcare. Our search is conducted on two prominent resource libraries, i.e., ScienceDirect and Scopus, for scientific literature which cover most of the BD for healthcare applications. Although it is not strictly limited, we basically used the keywords "*big data*" and "*health*" and "*4.0*" to steer the search. Once all papers are gathered, we implemented a two-step screening process for selecting the final set of papers. In the first step, we examined the titles, abstracts, and keywords of the papers for obtaining the initial set of relevant papers. Next, all papers within this set were examined in detail, and the final set of papers that address the topic were selected for the review.

In an effort to provide as much information as possible from the existing immense body of literature, we analyzed the selected papers in multiple dimensions. We believe that these dimensions summarized below, elicit the impact and relevant information of each study comprehensively.

- **Year:** Year of the publication.
- **Country:** The country where the study was made. If not reported, country of the first author is considered.
- **Publication:** The name of the publication (journal, conference, book) where the paper was published.
- **Decision problematic:** The research question or decision problem tackled in the study.
- **Application area:** The area to which the proposed approach was applied.

- **Methods and tools used:** Basic methods and tools utilized to achieve the objective of the study.

As previously mentioned, our main ambition in this survey is to reveal the application areas of BD in healthcare in the context of Industry 4.0, discuss challenges, and draw future research directions. Therefore, in the next section, we mostly focused on and discussed application-oriented papers rather than the theoretical ones.

## 3. Literature review

In this section, we group the papers included in our survey with respect to their application domain and/or the technology implemented. For this purpose, we first provide an overview of the most prominent survey papers in the BD for healthcare domain in Section 3.1. Next, we discuss studies as which focus on BD implementations on specific diseases in Section 3.2, general IoT implementations in healthcare in Section 3.3, use of smart sensors and wearable devices in Section 3.4, patient data privacy and security in Section 3.5, techniques and approaches for fusing data collected from multiple and heterogeneous sources in Section 3.6, use of BD applications for improving health an safety of individuals in workplaces and/or at homes in Section 3.7, approaches adopted for developing healthcare system frameworks in Section 3.8, mobile app implementations for healthcare in Section 3.9, and finally approaches used for measuring healthcare quality in Section 3.10

### 3.1. Survey & review papers

Among the many survey and/or review papers in the field of interest, Lbrini, Fadil, Rhinane, and Oulidi (2019) attempted to quantify the literature on "Big Health Data". Their review revealed that the most investigated big health data related topic was in "oncology" domain while remote sensing and monitoring are other important and hot topics. In another study, da Silveira, Neto, Machado, da Silva, and Amaral (2019) provided a review of Industry 4.0 applications regarding health sector. They identified main technologies used in *Health 4.0* and discussed their descriptive characteristics. Aceto, Persico, and Pescapé (2020) systematically surveyed and analyzed how new technologies such as IoT, CC, fog computing (FC), and BD change the nature of e-Health and its ecosystem. They also discussed the main application scenarios, benefits, cross-disciplinary challenges, and lessons learned from these applications.

Aceto, Persico, and Pescapé (2018) presented a survey by discussing the role of Information and Communication Technologies (ICT) in healthcare. They also provided a timely picture of novel healthcare applications utilizing ICT. In another study, Maina and Singh (2020) implemented an exploratory study regarding e-Health strategies of African countries. In their study, they particularly presented successful e-Health programs and aimed to find an answer for the question: why national e-health strategies matter? (Rizwan, et al., 2018) reviewed the technologies, in particular, nano-sensor and nano-communication network technologies, that generate the healthcare data. They discussed the significance and analytical capacities of these technologies in terms of enabling P4 (predictive, preventive, personalized, and participatory) healthcare systems. They also proposed a BD analytics framework comprising of three layers, namely, (*i*) data source layer, (*ii*) enabling technologies layer for data collection and processing, and (*iii*) analytics engine layer consisting of ML algorithms.

Mshali, Lemlouma, Moloney, and Magoni (2018), on the other hand, surveyed the Health Monitoring Systems (HMS) that aim to provide timely e-health services to individuals so that the pressure on the health system can be reduced. They provided the state-of-the-art for HMS with a particular focus on their application to elderly people. They also summarized the most important functions and services provided by HMS and discussed challenges and open issues in this field. In another review Pramanik, Lau, Demirkan, and Azad (2017), the authors presented a detailed analysis of BD analytics and smart systems in the context of healthcare services. They also proposed a BD-driven smart healthcare system framework. In Darwish, Hassanien, Elhoseny, Sangaiah, and Muhammad (2019), the researchers reviewed the impact of IoT and CC technologies and their hybrid use in healthcare systems.

Some other recent review and survey papers which tackle in the field of BD and healthcare include (Sisodia & Jindal, 2021), Balogun, Tella, Baloo, and Adebisi (2021), Divekar, Itankar, and Malge (2021), Abdel-Basset, Chang, and Nabeeh (2021), (Mustapha, Khan, Qureshi, Harasis, & Van, 2021), Krishnamoorthy, Dua, and Gupta (2021), and González, Vásquez, Uribe, and Hernández (2021). In Sisodia and Jindal (2021), for example, the authors provided a detailed review of studies in a meta-analytic framework for health sector and concluded that the number of studies (most of which use BD analytics) that implement Industry 4.0 in healthcare is limited. They also mentioned that budget, specialized staff and security are the most prominent limitations in applying Industry 4.0 concepts in healthcare. Balogun et al. (2021) reviewed studies which incorporate BD and ML approaches for analyzing the climate change and air pollution which directly affect human health. Divekar et al. (2021), on the other hand, considered the COVID-19 pandemic outbreak and presented a review of studies which implemented Industry 4.0 based tools including ML, BD, IoT and AI to analyze the impact of disease to public.

### 3.2. Disease-specific studies

In our review of the literature, we have encountered several papers which target utilizing BD to systematically extract information from data sets or improve services related to specific diseases such as diabetes, COVID-19, heart diseases, sleep health disorders, tuberculosis, myopia, etc.

As an example, with the objective of constructing a set of representative variables for BD regarding a patient's health prediction, Kaschel, Rocco, and Reinao (2018) proposed an algorithm for the systematic assessment of readmission predictors on diabetic patients. They demonstrated the efficiency of their algorithm on ten years worth real data of diabetic patient records obtained from the American Diabetes Association. In another study, Benaim, et al. (2020) carried out a cross-hospital study to validate the results obtained from synthetic data in various clinical research projects. With this approach they assessed the accuracy and precision of statistical estimates for the results obtained from synthetic structured data for diabetic patients. Similarly, Musacchio, et al. (2020) considered diabetic patients and discussed the advantages of using AI and BD to assist diabetologists in managing healthcare services. Considering the recent developments in wireless networks, BD technologies, and IoT, Chen, et al. (2018) aimed to design sustainable, cost-effective, and intelligent solutions for personalized diabetes diagnosis. In particular, their design comprises of smart clothing, smart phone, and BD clouds. They also conducted an experiment which shows that their design is effective in terms of providing personalized diagnosis and treatment suggestions to patients.

There also exist studies which analyzed the impact of BD implementations during the COVID-19 pandemic. In their paper, Abdel-Basset et al. (2021) proposed an intelligent framework which employs disruptive technologies such as AI, Virtual Reality (VR), Augmented Reality (AR), IoT, Internet of Medical Things (IoMT), BD, that are essential for Industry 4.0 development for analyzing COVID-19 cases and resources. In particular, the authors sought to provide a roadmap for governments and healthcare organizations for adopting these technologies to reduce the negative impact of such outbreaks for COVID-19. In another work, Bragazzi (2020) highlighted the importance of BD analytics and AI-based techniques in enabling fast and reliable detection of Corona virus during the COVID-19 pandemic. They also stated that Industry 4.0 tools assist decision makers in tracing cases and improving public health monitoring at the molecular and micro-level.

In Joloudari, et al. (2020), the authors implemented ML techniques of Random Trees (RTs), Support Vector Machines (SVM), and decision tree of Chi-squared Automatic Interaction Detection (CHAID) to enhance the accuracy of coronary heart disease diagnosis by selecting the most significant predictive features. Dias, Dias, Barboza, Sobrinho, and Santos Filho (2018) presented and discussed a medical decision support system that can help detect potential adverse events in the cardiovascular system before they happen. The system comprises of heart and Ventricular Assist Device (VAD) that collects data from the body and a cloud information system that conducts BD analytics and simulations to provide preventive medical decision support. They emphasized the importance of collecting real time data rather than obtaining it at the moment of query for an effective medical decision support.

Sleep monitoring and sleep health is another topic studied by several scholars in the context of BD implementation and Industry 4.0 revolution. Obtrusive Sleep Apnea (OSA) is a sleep disorder that has adverse effects on quality of life such as personality disorders and reduced psychomotor performance. Considering these adverse effects, Yacchirema, Sarabia-Jácome, Palau, and Esteve (2018) presented a system that monitors factors of patients such as sleep environment, sleep status, physical activities, and other relevant open data that are available through smart cities for both detecting and supporting of the treatment of OSA. They utilized FC and ML for analyzing the data and generating recommendations for the treatment. Similarly, in Hong and Yoon (2017), the authors employed deep learning (DL) and techniques to generate accurate sleep pattern classification of patients. Ammae, Korpela, and Maekawa (2018) used commercially available Wi-Fi modules integrated with a novel ML-based unobtrusive method to detect body movements of patients during sleep.

Focusing on infectious diseases such as tuberculosis, Sudana and Emanuel (2019) investigated the possible usage of BD to monitor and prevent spread of infectious diseases. In particular, they surveyed solutions proposed in the literature and discussed that the scope of prevention should include monitoring and analyzing the clinical data, early warning via monitoring daily activity data as well as and patients' vital signs.

To improve the performance of training algorithms used in DL and AI that support clinical decision making, Nind, et al. (2020) developed an extensive software platform to manage BD of radiological data extracted from the whole Scottish population. Heude, et al. (2019) utilized a BD approach to produce descriptive anthropometric references and to validate and develop new national pediatric growth charts for in the presence of large data sets of physical growth measurements. Silva, Zilberman, Romero, Pineda, and Herazo-Beltran (2020) aimed to identify patterns for external fatal injuries. Considered as a global health problem, these injuries are caused by intentional or unintentional events such as trauma, assault, accidents, or suicide. In their study, they utilized data mining (DM) techniques, in particular a decision tree-based classification model, to detect patterns inherent in these injuries. Parsons and Duffield (2020) focused on paradigm shift toward digital neuropsychology due to use of BD and emerging technologies. They asserted that innovative technologies will lead to a paradigm shift from data-poor behavioral science to data-rich science that will also have implications toward ethical and legal mandates. Having said that, they provided a review of neuropsychological technologies and the potential use of methodologies/technologies such as DL, simulation, and tools for data monitoring. Lin, et al. (2018) utilized ML and BD to predict myopia development among Chinese school-aged children. By using the refraction data from electronic medical reports, they used the RF algorithm to train the data. With the developed methodology, it is possible to diagnose children that are likely to develop myopia in adulthood.

### 3.3. IoT implementations

The IoT technologies, on the other hand, enabled designing complete ecosystems which involve wearable smart sensors and cloud services through the IoT infrastructure. In other words, IoT approach permits the use of BD from different sources to be fused and analyzed with the purpose of diagnosing patients more accurately.

Based on these technological developments, Rahmani, et al. (2018) presented a practical solution and a concept of full-system of cloud services to take advantage of FC in IoT-health systems. Similarly, Trinugroho and Baptista (2014), adopted the IoT infrastructure in the healthcare domain and proposed a patient-centric healthcare service structure where numerous portable and wearable medical devices as well as cloud-based services are deployed to enhance the quality of patient life. In accordance with the work of Trinugroho and Baptista (2014), da Costa, Pasluosta, Eskofier, da Silva, and da Rosa Righi (2018) highlighted that patient-centric healthcare approaches are critical and proposed possible future directions for combining patient data in the hospital to enhance the effectiveness and efficiency of services. Hossain and Muhammad (2016) also developed a BD framework for collecting, analyzing, classifying and storing data obtained from a variety of sources in healthcare domain.

Considering the challenge of managing BD for healthcare services in CC and the IoT paradigm, Elhoseny, et al. (2018) developed a model which optimizes virtual machine selection in cloud-IoT health services applications. Using the data input from nonhuman intervention systems, such as sensor data, the authors sought to improve and efficiently manage the performance of healthcare systems by reducing operational execution time and optimizing patient data storage. In an interesting study, Qadri, Nauman, Zikria, Vasilakos, and Kim (2020) discussed the future of IoT. Stating that the impact of IoT on the advancement of the healthcare industry is immense, they surveyed the emerging technologies that transform the healthcare IoT. They classified the application frameworks of healthcare IoT as (*i*) cardiovascular diseases, (*ii*) neurological disorders, (*iii*) ambient assisted living, and (*iv*) fitness tracking. Similarly, Ahamed and Farid (2018) discussed the role of IoT and ML in personalized healthcare and classified their roles as: (*i*) diagnostics, (*ii*) assistive, and (*iii*) monitoring. The authors emphasized that the evaluations or recommendations made by ML largely depend on the accuracy of the data set. Thus, the data should be free from human biases as much as possible and special attention should be given to data accuracy and integrity.

Manogaran, et al. (2018) proposed a new architecture of IoT and BD ecosystem for handling healthcare data. In particular, the architecture comprises of two sub-architectures: (*i*) Meta Fog-Redirection (MF-R) architecture for collecting and storing data from various devices, and (*ii*) Grouping and Choosing (CG) architecture for securing the collected data. The framework is also used for predicting the hearth diseases by utilizing ML. There are several other novel studies such as Farahani, et al. (2018), and Rahmani, et al. (2018), Woo, Lee, and Park (2018), Adame, et al. (2018), and Pagán, Zapater, and Ayala (2018) which attempted to integrate IoT technologies with BD analytics for smarter and efficient healthcare services. Adopting different perspectives, those studies mainly seek to utilize wearable sensors, body sensor networks, CC for the sake of improved healthcare services.

As a different perspective, Panzarasa, Griffiths, Sastry, and De Simoni (2020) introduced the concept of social medical capital that corresponds to utilizing relational data from social media to improve patients' self-care and health. They asserted that relational data obtained from social media where patients and caregivers interact may provide invaluable benefits via network science and BD analytics. To achieve this goal, the authors proposed promoting the participation of both patients and caregivers in online health communities as well as appropriate training programs. In Sahoo, Mohapatra, and Wu (2016), the authors designed a probabilistic data collection mechanism for a cloud-based healthcare system. Based on the collected data, they performed a correlation analysis to detect relations between health parameters and diseases. Then a stochastic prediction model is developed to predict the future health condition of patients based on their current status. Performance of the proposed framework is evaluated with extensive simulations in the cloud environment.

### 3.4. Smart sensors and wearables

In traditional systems, patient data including vital signs are routinely collected by standalone medical devices manually. The introduction of IoT technology and BD enabled continuous monitoring of patients' health status and vital signs via smart devices, smart sensors as well as smart wearables. The big health data collected by these devices also improved the accuracy of predictions related to the health status of individuals. Moreover, such applications can also be regarded as preventive healthcare tools that are used for increasing the early diagnosis probability and reducing the risk of serious illnesses. With this, they help improving to the quality of patients lives during treatments (Dogan, Karatas, & Yakici, 2019). The smart wearable applications in hospitals are studied by several researchers. Some of the most common parameters that are monitored by those devices include heartbeat, body temperature body mass, step count and sleep quality.

Among the papers which consider the use of smart sensors and/or wearables, Massaro, Ricci, Selicato, Raminelli, and Galiano (2020) implemented AI techniques such as SVM and Long Short Term Memory (LSTM) algorithms and developed a Decision Support System (DSS) for health wearable sensors which use BD analytics and monitor health status of users. These devices assist decision makers in generating multi-dimensional risk map of patients by providing them with more and accurate health data with less cost and effort. In another interesting study, Mattsson, Partini, and Fast-Berglund (2016) presented a multi-dimensional human performance measurement approach by using BD collected by multiple digital devices. With the study, the authors demonstrated how new technologies can enhance the health and safety of humans in a work place. Additionally, they discussed the advantages of combining physiological data with other work environment data of operators.

Asthana, Megahed, and Strong (2017) developed a recommendation engine that provides personalized advice regarding which wearables and IoT solutions to use for health monitoring. The engine utilizes the medical history of a person that comprises all diseases that this person is at risk of. For this purpose, a text mining algorithm is used to analyze the medical history of the person while her/his demographic attributes are also fed to a ML algorithm to predict the possible diseases. The recommendation phase is conducted via employing a mathematical optimization model. Considering that sudden cardiac arrest out-of-hospital has a low survival rate, ElSaadany, Majumder, and Ucci (2017) proposed a wireless early prediction system of cardiac arrest through IoT. In their implementation, they utilized a smart phone as the platform for developing an embedded system for predicting hearth attacks. The system uses wearable low energy devices to collect the required data such as hearth rate and body temperature. Then the data are transmitted to a smart phone and analyzed for predicting a possible hearth attack.

Wu, Wu, and Yuce (2019) focused on reducing health risks in the construction industry and presented a hybrid wearable sensor network system to improve the safety of the working environment. The environmental data (i.e., temperature, humidity) and vital signs of individuals (i.e., hearth rate, body temperature) are collected from low energy sensors and transmitted to a gateway. While gateway can serve as a local server for triggering alerts, it can also transmit the collected data to a cloud server for data storage or further analysis. Catarinucci, et al. (2015) proposed a Smart Hospital System (SHS) that employs technologies such as Radio Frequency Identification (RFID), Wireless Sensor Network (WSN), and smart mobile devices. In the system, real-time environmental and patient data are collected with these technologies and transmitted to a control center where a monitoring application makes these data accessible within the hospital.

### 3.5. Data privacy & security

One other important aspect of the use of IoT technologies in managing patient data is the security of personal patient information. Data obtained by IoT technologies can be private or public. During the COVID-19 pandemic, for instance, abundant public and private data have been collected via IoT technologies to mitigate the ill effects of the pandemic. Within public data sets, which essentially consist of aggregated data, privacy has lesser importance since the data usually lacks the identity of the individuals. Private data, conversely, include identity information of the patients. During the COVID-19 pandemic, the majority of data have been obtained via mobile devices or wearables where the consent of the user regarding the data collection process is usually obtained via an undertone agreement or the consent of the user is not taken at all. This fact has led to joint efforts of governments, data providers, and researchers for developing protocols and regulations that provide ethics clearance in the process of data sharing and manipulation (Hu, et al., 2021). To that end, many researchers have focused on recoding and identity hiding procedures to make private data anonymous (Cerf, et al., 2017; Pelekis, et al., 2012; Primault, Mokhtar, & Brunie, 2015).

Other studies such as Yang, Zheng, Guo, Liu, and Chang (2019), Yang, Zheng, Guo, Liu, and Chang (2018), and Zhang, et al. (2015) tackled the security issue aroused by such systems in healthcare services. These studies proposed novel security systems and privacy-preserving e-health systems to preserve the confidentiality of patients healthcare data. Since full-face photographic images are regarded as protected health information, Jeong, Yoo, Kim, and Shim (2020) developed a methodology based on ML and BD that extracts personal information and facial features from the data. Anonymizing the data by removing personal data of patients also enables sharing the data securely for secondary research.

In the future, data privacy and security will continue to be an important aspect of the IoT based healthcare. As the IoT based healthcare services evolve toward personalized healthcare, anonymizing and recoding data as well as identity hiding techniques will draw more attention of the researchers.

### 3.6. Data fusing

With the introduction of IoT and BD implementations, the extraction of important patient data and fusing it became another research topic for scholars. Considering the big health data obtained from a set of heterogeneous healthcare devices and smart wearables, Kalamkar et al. (2020) sought to develop better ways using ML to fuse data for assessing healthcare applications.

Traditional Chinese Medicine (TCM) and intelligent use of it have played a crucial role in the prevention and reducing the spread risk of the coronavirus pneumonia (COVID-19) (Zheng, et al., 2020). Hence, Fong, et al. (2017) proposed a concept of fusing the mobile application software technology, BD, sensing technology, and ML for TCM-oriented monitoring and assessment of healthcare. Emphasizing the benefits of TCM for developing a set of practical and thorough health care system that is closely related to daily lifestyles, they proposed a TCM-based framework involving sensing, monitoring, time-series and image analysis, and lifestyle app.

As an interesting study, Mackey, et al. (2020) used public streaming platforms such as Twitter for data collection. After the outbreak of COVID-19 pandemic, concerns have been raised for underreporting due to the lack of adequate testing kits, overburdened health system, failure to report or test a suspected death, etc. To hedge against these concerns, they conducted a study where they collected user-generated conversations from Twitter that are believed to be associated with COVID-19 symptoms, experiences, and disease recovery. Then, these data are clustered via unsupervised learning techniques and analyzed.

### 3.7. Improving health and safety in the workplace and at home

BD and smart systems have also been applied to facilitate workplaces and homes while monitoring the health status of workers, elderly and patients. Temperature, humidity, and carbon dioxide levels affect medical health of workers and their comfort. Hence, keeping these factors at their nominal levels is important for a productive and healthy working environment. Taking this fact into account, Molka-Danielsen, Engelseth, and Wang (2018) considered integration of large-scale WSN technologies for monitoring air quality of workplaces. In this respect, they proposed a systems analytics approach for utilizing BD for visualization and monitoring the status of an industrial workplace. Similarly, Lin, Cheng, and Jiang (2020) attempted to improve health of workers in Taiwan by investigating the laws and regulations promulgated in Taiwan. Using BD obtained from keyword searches in the Google Trends platform related to working conditions, the authors suggested a number of policy changes.

Garcés, Oquendo, and Nakagawa (2019), on the other hand, proposed a systems-of-systems software architecture for supportive health care at home. They stated that supportive health care at home gains growing attention lately due to the growth of diseases and disabilities and avoidance of long-term hospitalization. In the software architecture, each constituent system such as electronic health record systems, smart devices and rehabilitation systems possesses independence while collaborating for the global mission.

Pang, Yang, Khedri, and Zhang (2018) discussed various technologies utilized for biomedical engineering and health informatics and presented an example pertaining to caregiving homes. In this particular example, the established system integrates various smart devices with heterogeneous but inter-operable communication networks. These devices collect detailed data about health and condition of residents. Tingay, Roberts, and Musselwhite (2018) emphasized that the social environment of an individual has a dramatic effect on both physical and emotional health. Hence, they considered that creating households may provide valuable information for understanding the social environment. For this purpose, they describe a method for creating household and sharing that information via large-scale linked data banks.

### 3.8. Developing a healthcare system framework

Some researchers adopted a more holistic approach and proposed novel healthcare system frameworks that incorporate BD-driven Industry 4.0 concepts. Among those studies, Alamri (2019) proposed a cloud-based BD analytics system for patients having chronic diseases. The system is comprised of three layers: (*i*) data acquisition, (*ii*) cloud BD analytics, and (*iii*) application layer. In the acquisition layer, the data regarding patients' medical history and patients' condition (via IoT sensors) are collected. Then these data are compressed, stored, formatted, and analyzed in the cloud BD analytics layer. This layer provides both real-time analysis and predictive analysis. Lastly, the cloud application layer provides the interface between the health network and the users. Via this layer, the sensors are controlled and the data are presented visually.

Ma, Wang, Yang, Miao, and Li (2016) proposed a big health application system based on IoT and BD. The proposed system consists of (*i*) a health perception layer, (*ii*) transport layer, and (*iii*) big health cloud service layer. The health perception layer collects human health associated data via sensors. Using various network technologies, the transport layer sends the instructions of the upper applications to sensors while collecting data obtained by the perception layer. Above all layers, the big health cloud service layer compiles, compresses, stores, formats, and analyzes the health data. In their paper, the authors also discussed possible applications of the big health system.

Pang, et al. (2015) presented an architectural framework for in-home healthcare services based on IoT. Business model, device and service integration architecture, and information system architecture components are integrated and aligned in the framework. In order to show the applicability of the framework, a prototype solution called iMedBox is developed. The iMedBox system successfully integrated in-home healthcare devices and services. In a similar study, Moraru, et al. (2018) developed tools for home assisted elderly people as well as their caregivers to enhance the performance of data analysis and design of cloud services within IoT implementations.

### 3.9. Mobile apps for healthcare

Healthcare operations and services can also benefit from having mobile apps. These apps permit hospital managers, doctors to track their patients, send /receive health reports in real-time. In other words, mobile apps improve the quality of service and communication between patients and caregivers. Inomata, et al. (2020) focused on contact lens associated dry eye and aimed to quantify and stratify individual subjective symptoms by using a mobile application called DryEyeRhythm and ML. In particular, the DryEyeRhythm application was used to collect data from patients and univariate and multivariate risk factors are determined via logistic regression. The study

Among the studies which incorporate the use of smart sensors, Kansara, Bhojani, and Chauhan (2018) proposed a smart wearable device which can be embedded in any type of fabric that uses health data collected via mobile applications to measure the sugar level of a person. Robbins, et al. (2020) attempted to identify and analyze sleep trends in terms of duration and quality. For this purpose, the authors used BD related to the sleep cycles of 2 million people in New York City via a popular mobile sleep app. Their results revealed a comprehensive evaluation of the sleep trends of the population with respect to seasonality, age, and sex.

### 3.10. Measuring healthcare quality

Current trends in BD analytics as well as other Industry 4.0 related healthcare information technologies are moving toward more complex models, frameworks, and tools (Sukumar, Natarajan, & Ferrell, 2015). With these developments, extracting higher quality data and healthcare quality measurement is receiving attention from several researchers.

Among those, Nantschev, Hackl, and Ammenwerth (2019) considered the problem of measuring healthcare quality and proposed a systematic methodology which includes expert interviews, identification of influencing factors and scenarios on routine clinical data. They seek to develop a model to utilize clinical routine data in assessing the quality of care for patient safety. Focusing on the mental health departments in Italy, Mattei (2019) investigated the innovation and creativity in psychiatry. The author suggested several ways to improve the psychiatry system by Industry 4.0 concepts and measure the quality of health services.

Al-Jaroodi, Mohamed, and Abukhousa (2020), on the other hand, discussed the impact of the Health 4.0 and related concepts (e.g., Internet of Health Things (IoHT), medical Cyber–Physical Systems (MCPS), ML, BD, health cloud, blockchain) to the healthcare industry and propose service-oriented strategies to improve the efficiency of Health 4.0 applications in the future. As an interesting study, through BD analysis, Park, Ahn, Kim, and So (2020) attempted to determine the perception of sports and physical activity in Korean adolescents. The authors utilize ten years worth of data and utilize text mining and Social Network Analysis (SNA) to investigate the data.

In Prashanthi, Deva, Vadapalli, and Das (2020), the authors discussed the importance of unused and unstructured healthcare data and state that such data constitutes approximately 80% of the generated data. Motivated by this fact, they propose a ML to investigate unstructured BD in healthcare systems with the objective of revealing and optimally utilizing information and improving healthcare quality.

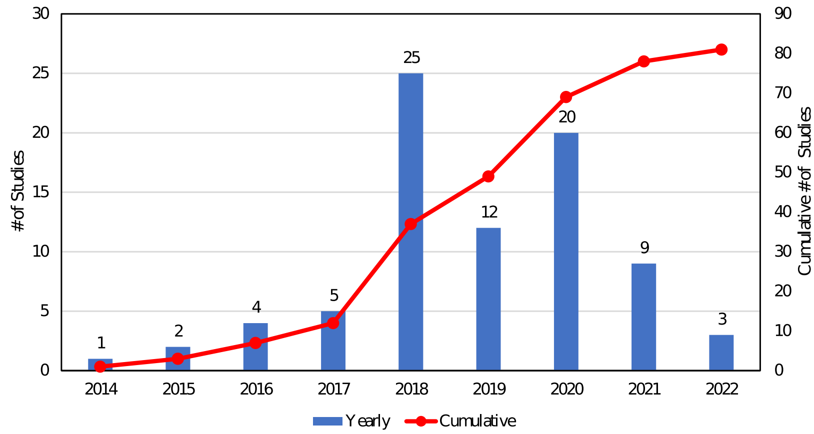


**Fig. 2.** Yearly and cumulative yearly number of studies.

## 4. Discussion

In this section, we first provide quantitative information regarding the reviewed studies according to the review dimensions. Next, we discuss the literature based on methods and tools implemented and application areas.

Fig. 2 reports the yearly number of related papers published. In the figure, the bars and solid line represent the number of published papers in particular years and cumulative number of papers, respectively. The figure reveals that there is a growing interest to BD implementations in the healthcare domain, especially after 2017. Among the 81 studies included in this survey, 69 of them are published between 2018 and 2022. As of the current year 2022, we have found only three relevant paper in the subject of interest, however, more papers are expected to be published during the year.

Figs. 3 and 4, on the other hand, show the number of studies published with respect to the origin of the country and continent, respectively. The figures show that USA and India, being the origin country of 10 studies is the leading country, followed by China and Italy. As also indicated in Kuo, Shyu, and Ding (2019), USA's Industry 4.0 implementation policies mostly tend to focus on public services, demand-side policy as well as education and training fields. China, on the other hand, tends to favor mostly environmental and public service policies for China. Regarding the continents as the origin of articles, Asia is the origin of 34 out of 81 studies included in this paper. Asia is followed by Europe (22 studies), America (16 studies), Africa (6 studies), and Australia (3 studies).

Table 1 reports the journals with decreasing order of the number of articles published in. According to the table, Future Generation Computer Systems, IEEE Access and Journal of Medical Internet Research are the top three journals with 10, 6, and 5 articles published, respectively. International Journal of Environmental Research and Public Health, JMIR Public Health and Surveillance, Journal of Industrial Information Integration, Technological Forecasting and Social Change, and Journal of Ambient Intelligence and Humanized Computing are the next three journals with 2 published articles in the domain. The results also depict that most of the journals which published articles concerning BD implementations in healthcare are peer-reviewed journals in computer science, medical, information, and engineering domains. Similarly, Table 2 reports the name of the conferences in which 16 out of 82 studies are presented.

Table 3 reports the frequency of studies with respect to their application areas. The table reveals that papers concerning the development and/or improvement of e-health systems have been frequently addressed by the studies. The term "e-health" is defined as "the use of ICT for health" by the World Health Organization (WHO) and it is generally adopted to enhance the efficiency, effectiveness, capacity and quality of healthcare services (Norgaard, et al., 2015). It mainly seeks to produce faster and easier access to services for both patients and healthcare providers. With the use of BD and Industry 4.0 implementations the research in e-health systems domain improved significantly by the inclusion of patients and e-health professionals.

We also observed that studies tackling specific diseases and the problem of improving workplace safety and health are also popular in the field. Recall that the main purpose of Industry 4.0 and related

**Table 1**
The number of yearly studies published in different journals.

| Journal | Frequency |
|---|---|
| Future Generation Computer Systems | 10 |
| IEEE Access | 6 |
| Journal of Medical Internet Research | 5 |
| International Journal of Environmental Research and Public Health | 2 |
| JMIR Public Health and Surveillance | 2 |
| Journal of Industrial Information Integration | 2 |
| Technological Forecasting and Social Change | 2 |
| Journal of Ambient Intelligence and Humanized Computing | 2 |
| Artificial Intelligence In Medicine | 1 |
| Enterprise Information Systems | 1 |
| Expert Systems with Applications | 1 |
| Future Internet | 1 |
| GigaScience | 1 |
| IEEE Communications Magazine | 1 |
| IEEE Communications Surveys & Tutorials | 1 |
| IEEE Internet of Things Journal | 1 |
| IEEE Reviews in Biomedical Engineering | 1 |
| Information Sciences | 1 |
| International Journal of Industrial Ergonomics | 1 |
| International Journal of Population Data Science | 1 |
| JMIR Formative Research | 1 |
| JMIR Medical Informatics | 1 |
| Journal of Medical Internet Research | 1 |
| Journal of Network and Computer Applications | 1 |
| Journal of Psychopathology | 1 |
| Journal of the Brazilian Computer Society | 1 |
| MedInfo | 1 |
| PLOS Medicine | 1 |
| Procedia CIRP | 1 |
| Sensors | 1 |
| Engineering Applications of Artificial Intelligence | 1 |
| Advanced Engineering Informatics | 1 |
| Urban Climate | 1 |
| Journal of Physics: Conference Series | 1 |
| International Journal of Interactive Mobile Technologies | 1 |
| Revista Venezolana de Gerencia | 1 |
| Applied Intelligence | 1 |
| Journal of Primary Care and Community Health | 1 |
| EAI/Springer Innovations in Communication and Computing | 1 |
| The Lancet Digital Health | 1 |
| **Total** | **63** |

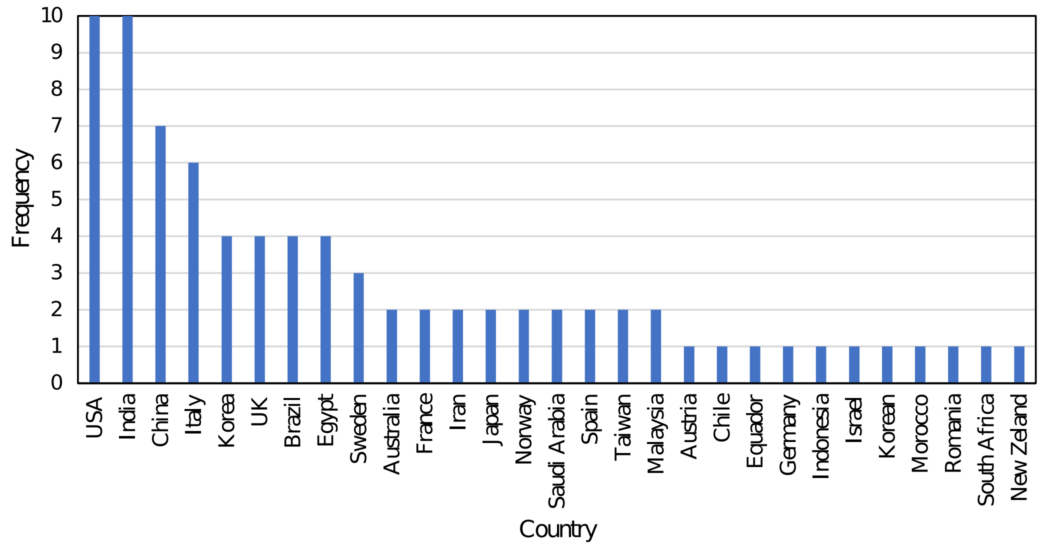


**Fig. 3.** Number of studies with respect to countries.

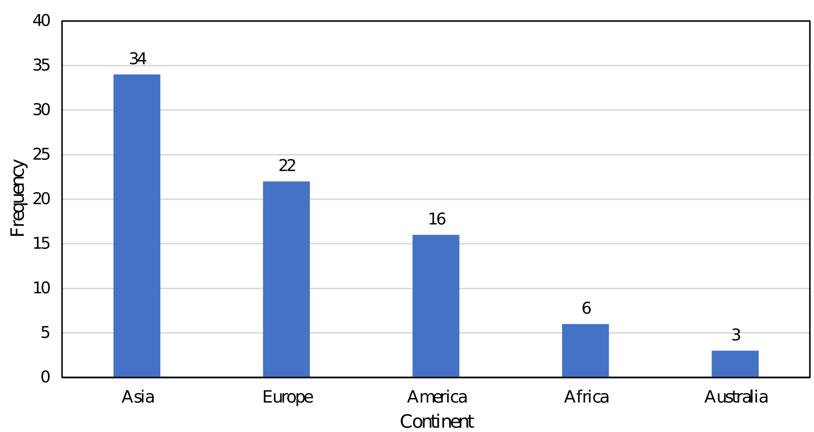


**Fig. 4.** Number of studies with respect to continents.

**Table 2**
List of conferences.

| Conference |
| --- |
| 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom) |
| 2018 International Conference on Machine Learning and Data Engineering (iCMLDE) |
| 2018 International Conference on Smart City and Emerging Technology (ICSCET) |
| 2018 International Symposium in Sensing and Instrumentation in IoT Era (ISSI) |
| 2019 International Conference on Platform Technology and Service |
| 2020 IEEE International Workshop on Metrology for Industry 4.0 & IoT |
| 2020 International Conference on Electrical and Electronics Engineering |
| 2020 International Conference on Industry 4.0 Technology (I4Tech) |
| 5th International Conference on Geoinformation Science |
| Doctoral Conference on Computing, Electrical and Industrial Systems |
| IEEE 41st Annual Computer Software and Applications Conference |
| IEEE 6th International Conference on AI & Mobile Services |
| IEEE International Conference on Automation |
| International Conference on Bioinformatics, Biotechnology, and Biomedical Engineering |
| International Conference on World Wide Web Companion |
| The 5th International Workshop on Big Data and Networks Technologies (BDNT) |

technologies is to create a smart and self-regulating industrial value via integrating CPS into different manufacturing service domains. Therefore, the paradigm of Industry 4.0 leads to a more effective, intelligent and faster decision-making process, which also considerably influences the health and safety of workers. With various implementations, it yields safer and healthier work environments. In particular, smart safety technologies, smart devices, BD, and IoT help decision makers in assessing, managing, and analyzing risk better (Polak-Sopinska, Wisniewski, Walaszczyk, Maczewska, & Sopinski, 2019).

There also exist several studies which consider the use of BD and Industry 4.0 tools to enhance the life quality of diabetic patients as well as the management of related healthcare services. These works mostly focus on extracting information systematically from diabetic

**Table 3**
The number of studies published with respect to application areas.

| Application Area | Frequency |
|---|---|
| e-Health systems | 24 |
| Work place safety and health | 5 |
| Diabetes | 4 |
| Pandemics | 4 |
| Smart applications | 3 |
| Cardiovascular system | 3 |
| Health data mining | 3 |
| Caregiving home systems | 2 |
| Healthcare data security | 2 |
| Alzheimer | 1 |
| Anthropometry | 1 |
| Clinical data fusion | 1 |
| External fatal injuries | 1 |
| Infectious diseases | 1 |
| Inpatient fall risk | 1 |
| Mental health | 1 |
| Myopia | 1 |
| Neurological disorders | 1 |
| Neuropsychology | 1 |
| Nursing services | 1 |
| Obtrusive Sleep Apnea (OSA) | 1 |
| Ophthalmology | 1 |
| Pathology | 1 |
| Radiology | 1 |
| Cancer diagnosis | 1 |
| **Total** | **66** |

**Table 4**
The number of studies published with respect to different methods and tools implemented.

| Methods and Tools | Frequency |
|---|---|
| IoT | 30 |
| BD | 25 |
| ML | 16 |
| DM | 6 |
| Wearable Devices | 6 |
| CC | 5 |
| Mobile Devices | 5 |
| AI | 4 |
| FC | 4 |
| Smart Devices | 4 |
| SNA | 3 |
| WSN | 3 |
| DL | 2 |
| RFID | 2 |
| Simulation | 2 |
| BDAI | 1 |
| CHAID | **1** |
| Cognitive Computing | 1 |
| VR | 1 |
| **Total** | **121** |

patients for further use in the domain. The focus on specific diseases can be regarded as part of the concept of patient-centric healthcare services. The traditional hospital-centric healthcare service systems which yield long waiting times in the hospitals and perform poorly in identifying serious illnesses in the early stages or dealing with chronic diseases are being gradually replaced by the patient-centric healthcare approaches (Zhang, et al., 2015). This new approach is critical to improve the quality of healthcare services both from the patient and hospital management perspectives by connecting the hospital, patients, and services with each other (Farahani, et al., 2018).

Smart applications, which are generally deployed on mobile devices, are also becoming more prevalent. Mobile devices, in particular mobile phones, have been important components of our life in recent years. Therefore, using them as platforms to monitor individual's health condition and process the data obtained have been a straightforward solution. We can observe signs of this provision in the developed applications. As the computational power and sensing capabilities of the mobile devices increase, we shall expect to have more smart health applications in our mobiles devices in the future.

In our review of the literature, we also investigate the most common methods and tools implemented in the research domain. Table 4 shows the frequency of studies published with respect to the methods and tools used. The table reveals that IoT, BD and ML implementations are commonly applied in the domain. We note that both Tables 3 and 4 do not include the survey and literature review studies. Use of IoT technologies assist decision makers to design holistic and more complete ecosystems of smart wearable devices and cloud services to improve healthcare services. BD management in healthcare applications, similarly, is another important research area since an effective data management policy improves the quality of healthcare services provided over the Internet.

In Tables 5 and 6, we provide a complete list of all studies. In particular table lists the year, origin country, application area, methods & tools implemented and the decision problematic tackled in each particular work included in this paper.

## 5. Conclusion and future outlook

This study is conceived as a reference aimed at helping researchers and practitioners research BD processing tools to meet the health sector's needs. Also, it should be a significant reference to other researchers in the field of health information systems and automation to effectively confront new concepts and approaches in the field of IT and effectively contribute to the evolution of Industry 4.0. BD in the industry has unique properties that are significantly different from BD in social networks and require special processing techniques. Based on the presented analysis, we can conclude that Industry 4.0 is an essential part of tomorrow's smart factories and smart hospitals, where software, technologies, and processes provide efficient results with significant minimization of time and costs. The IoT has significantly changed healthcare in a relatively short time. For example, connected devices provide significant support to older people and increase their safety in everyday environments. Additionally, connected devices help doctors consult with researchers worldwide on complex cases in real time, monitor patients' chronic diseases during breaks between some other activities, etc. Nevertheless, every advance in technology brings with it challenges that need to be overcome. This study aimed to highlight the status of research and possible future directions of development for different areas of application of Industry 4.0 in the healthcare sector.

Data-based innovations can affect all areas of social development, especially in the healthcare sector. However, to fully implement and exploit BD processing algorithms' potential, policy makers must develop coherent policies to use that data safely. This could be achieved by (*i*) supporting education focused on researching data processing algorithms, (*ii*) stimulating the necessary investment environment to develop BD technology, (*iii*) promoting the concept of open data and removing data silos, (*iv*) providing competitive technical infrastructure and (*v*) promoting balanced legislation while regulating issues such as privacy and security. Therefore, further and sustainable progress in BD-based innovation depends largely on the government's activities and vision in cooperation with other major stakeholders in the healthcare sector.

There are also some limitations in our study. Firstly, for each study included in our paper, we adopted a rather holistic perspective and introduced the application area, methods and tools used, and decision problematic and ignored the underlying specific problem types, procedures and structures. In this regard, the review dimensions could be augmented with others to elicit additional data in this topic. Secondly, we have not discussed the use and possible impact of blockchain

**Table 5**
Full list of studies included in the survey.

| # | Author(s) | Year | Country | Application Area | Methods & Tools | Decision problematic |
|---|---|---|---|---|---|---|
| 1 | Trinugroho and Baptista | 2014 | Norway | e-Health systems | IoT | Developing complete systems with smart devices and cloud services |
| 2 | Catarinucci, et al. | 2015 | Italy | e-Health systems | RFID, WSN, Smart Devices, IoT | Collecting environmental and patient parameters for a smart hospital system |
| 3 | Pang, et al. | 2015 | Sweden | e-Health systems | IoT, RFID, Mobile Devices, Wearable Devices | Architectural framework for in home healthcare services |
| 4 | Sahoo et al. | 2016 | Taiwan | Health data mining | CC, DM | Analysis of healthcare BD for predicting future health condition |
| 5 | Ma et al. | 2016 | China | e-Health systems | IoT, Mobile Devices, Wearable Devices, Cognitive Computing | Architectural framework for big health application system |
| 6 | Mattsson et al. | 2016 | Sweden | Work place safety and health | BD | Improving human health and safety at work place |
| 7 | Hossain and Muhammad | 2016 | Saudi Arabia | Pathology assessment | BD | Fusing data from multiple sources |
| 8 | Fong, et al. | 2017 | China | e-Health systems | WSN | Monitoring TCM-oriented healthcare assessments with mobile sensors |
| 9 | Asthana et al. | 2017 | USA | e-Health systems | Wearable Devices IoT | Recommending personalized wearable devices and IoT solutions |
| 10 | ElSaadany et al. | 2017 | USA | Cardiovascular system | IoT, ML, Mobile Devices | Early prediction system for cardiac arrest |
| 11 | Hong and Yoon | 2017 | Korea | e-Health systems | DL | Sleep monitoring |
| 12 | Pramanik et al. | 2017 | USA | Literature Review | Literature Review | Literature Review |
| 13 | Tingay et al. | 2018 | UK | Health data mining | DM | Creating households for BD research of health and wellbeing |
| 14 | Pang et al. | 2018 | China | Caregiving home systems | IoT Smart Devices | Monitoring health and condition data in caregiving homes |
| 15 | Molka-Danielsen et al. | 2018 | Norway | Work place safety and health | IoT, WSN | Monitoring air quality for workers' medical health |
| 16 | Lin, et al. | 2018 | China | Myopia | ML (Random Forest) | Applying BD and ML to predict the onset of high myopia |
| 17 | Dias et al. | 2018 | Brazil | Cardiovascular system | Simulation, BD | Medical decision support |
| 18 | Aceto et al. | 2018 | Italy | Literature Review | Literature Review | Literature Review |
| 19 | Chen, et al. | 2018 | China | Diabetes | Wearable Devices IoT, ML | Designing personalized diabetes diagnosis |
| 20 | Manogaran, et al. | 2018 | India | Healthcare data security | FC, CC, IoT ML | A framework for analyzing healthcare BD and providing data security |
| 21 | Rizwan, et al. | 2018 | UK | Literature Review | Literature Review | Literature Review |
| 22 | Yacchirema et al. | 2018 | Ecuador | Obtrusive Sleep Apnea (OSA) | Smart Devices FC, ML | Detecting and supporting treatment of OSA |
| 23 | Mshali et al. | 2018 | France | Literature Review | Literature Review | Literature Review |
| 24 | Ahamed and Farid | 2018 | Australia | e-Health systems | IoT, ML | Discussion on IoT and ML applications for personalized healthcare |
| 25 | Elhoseny, et al. | 2018 | Egypt | e-Health systems | BD, IoT, CC | Management of BD services |
| 26 | Kaschel et al. | 2018 | Chile | Diabetes | BD, DM | Generating predictor variables for representing BD |
| 27 | Kansara et al. | 2018 | India | Smart applications | BD | Measuring the sugar level of a person with wearable sensors |
| 28 | Rahmani, et al. | 2018 | USA | e-Health systems | IoT | Developing complete systems with smart devices and cloud services |
| 29 | Moraru, et al. | 2018 | Romania | Caregiving home systems | IoT | Improving the efficiency of IoT-based health monitoring systems |
| 30 | da Costa et al. | 2018 | Germany | e-Health systems | IoT | Developing complete systems with smart devices and cloud services |
| 31 | Yang et al. | 2018 | China | e-Health systems | BD, IoT, CC | Preserving security of patients healthcare data |
| 32 | Pagán et al. | 2018 | Spain | Neurological disorders | IoT | Workload balancing among data centers of IoT e-Health systems |
| 33 | Adame, et al. | 2018 | Spain | e-Health systems | IoT | Improving quality and access to healthcare |
| 34 | Ammae et al. | 2018 | Japan | e-Health systems | ML | Sleep monitoring |
| 35 | Woo et al. | 2018 | Korea | e-Health systems | IoT | Improving the reliability of IoT systems |
| 36 | Rahmani, et al. | 2018 | USA | e-Health systems | BD, IoT, FC | Improving the efficiency of IoT-based health monitoring systems |
| 37 | Farahani, et al. | 2018 | Iran | e-Health systems | BD, IoT, FC | Improving the efficiency of IoT-based health monitoring systems |
| 38 | Sudana and Emanuel | 2019 | Indonesia | Infectious diseases | BD | Preventing infectious diseases |
| 39 | da Silveira et al. | 2019 | Brazil | Literature Review | Literature Review | Literature review |

network technology in healthcare. Blockchain technology has a significant potential for future healthcare services where the patient is placed at the center of the ecosystem, while privacy, security, and interoperability of data are improved. This technology is expected to change the nature of the Healthcare Industry 4.0 and increase service quality significantly.

Studies surveyed give us insights and hints about the future perspectives of BD applications in Healthcare Industry 4.0. It is evident that the pace of developing technologies such as efficient algorithms and smart hardware is expected to pave the way for future BD healthcare applications. Among these applications, for instance, the concept of healthcare at home is expected to be more prevalent. As a side effect of better nutrition and better healthcare, the aging of world population is increasing. As a way to decrease the cost associated with the healthcare of the elderly and avoid unnecessary hospitalization, supportive systems for healthcare at home will be one of the main research topics in the future. In line with this point, we can easily assert that wearable devices, IoT, and cloud-based technologies will form the

**Table 6**
Continued of Table 5.

| # | Author(s) | Year | Country | Application Area | Methods & Tools | Decision Problematic |
|---|---|---|---|---|---|---|
| 40 | Cho and Jin | 2019 | Korea | Inpatient fall risk | ML | Developing a clinical decision support service to predict inpatient falling |
| 41 | Garcés et al. | 2019 | Brazil | e-Health systems | IoT Smart Devices | Healthcare supportive home system-of-systems |
| 42 | Wu et al. | 2019 | Australia | Work place safety and health | Wearable Devices IoT | Reducing health risks in the construction industry |
| 43 | Alamri | 2019 | Saudi Arabia | e-Health systems | IoT, CC Wearable Devices | Architectural framework for cloud-based disease diagnosis technologies |
| 44 | Heude, et al. | 2019 | France | Anthropometry | BD | Validation of pediatric growth charts |
| 45 | Lbrini et al. | 2019 | Morocco | Literature Review | Literature Review | Literature Review |
| 46 | Nantschev et al. | 2019 | Austria | Nursing services | BD | Measuring the quality of healthcare |
| 47 | Mattei | 2019 | Italy | Mental health | BD | Innovation in psychiatry |
| 48 | Yang et al. | 2019 | China | e-Health systems | IoT | Preserving security of patients healthcare data |
| 50 | Darwish et al. | 2019 | Egypt | Literature Review | Literature Review | Literature Review |
| 51 | Silva et al. | 2020 | India | External fatal injuries | DM | Determining patterns for external fatal injuries |
| 52 | Aceto et al. | 2020 | Italy | Literature Review | Literature Review | Literature Review |
| 53 | Mackey, et al. | 2020 | USA | Pandemics | ML, SNA (Twitter) | Using ML to extract data associated with COVID-19 on Twitter |
| 54 | Parsons and Duffield | 2020 | USA | Neuropsychology | DL, Simulation Mobile Devices | Digital Neuropsychology and High-Dimensional Neuropsychological assessments |
| 55 | Panzarasa et al. | 2020 | UK | e-Health systems | SNA | Social media-based patient health care |
| 56 | Inomata, et al. | 2020 | Japan | Smart applications | ML | Symptom diagnosis with mobile application and ML |
| 57 | Qadri et al. | 2020 | Sweden | e-Health Systems | IoT, AI | Survey of emerging technologies |
| 58 | Maina and Singh | 2020 | South Africa | Literature Review | Literature Review | Literature Review |
| 59 | Nind, et al. | 2020 | UK | Radiology | BD, AI, ML | BD management for healthcare |
| 60 | Benaim, et al. | 2020 | Israel | Diabetes | DM | Validation of synthetic health data |
| 61 | Musacchio, et al. | 2020 | Italy | Diabetes | BD, AI | Clinical decision making |
| 62 | Prashanthi et al. | 2020 | India | Ophthalmology | ML | Unstructured BD analysis |
| 63 | Park et al. | 2020 | Korean | Health data mining | DM, SNA | BDE |
| 64 | Kalamkar et al. | 2020 | India | Clinical data fusion | ML | Assessing healthcare applications |
| 65 | Joloudari, et al. | 2020 | Iran | Cardiovascular system | BD, ML, CHAID | Enhancing the accuracy of disease diagnosis |
| 66 | Jeong et al. | 2020 | Korea | Alzheimer | BD, ML | Protection of health information |
| 67 | Massaro et al. | 2020 | Italy | e-Health systems | BD, AI | Developing a decision support system to predict health status |
| 68 | Lin et al. | 2020 | Taiwan | Work place safety and health | BD | Improving human health and safety at work place |
| 69 | Robbins, et al. | 2020 | USA | Smart applications | BD | Analyzing sleep trends |
| 70 | Al-Jaroodi et al. | 2020 | USA | e-Health Systems | IoT, BD, Mobile Devices | Improving efficiency of Health 4.0 implementations |
| 71 | Abdel-Basset et al. | 2021 | Egypt | Pandemics | BD, AI, VR, IoT | Providing a roadmap for adopting disruptive technologies |
| 72 | Sisodia and Jindal | 2021 | India | Literature Review | Literature Review | Literature Review |
| 73 | Aheleroff, Mostashiri, Xu, and Zhong | 2021 | New Zealand | Work place safety and health | IoT, BD | Developing personalized face masks |
| 74 | Balogun et al. | 2021 | Malaysia | Literature Review | Literature Review | Literature Review |
| 75 | Divekar et al. | 2021 | India | Literature Review | Literature Review | Literature Review |
| 76 | Abdel-Basset et al. | 2021 | Egypt | Pandemics | IoT | Use of disruptive technologies for COVID-19 analysis |
| 77 | Mustapha et al. | 2021 | Malaysia | Literature Review | Literature Review | Literature Review |
| 78 | Krishnamoorthy et al. | 2021 | India | Literature Review | Literature Review | Literature Review |
| 79 | González et al. | 2021 | Brazil | Literature Review | Literature Review | Literature Review |
| 80 | Krishankumar, et al. | 2022 | India | Healthcare data security | BD | Cloud vendor selection for the healthcare industry |
| 81 | Sarfraz, et al. | 2022 | USA | Pandemics | BD | Optimization of vaccine manufacturing processes during and post the COVID-19 pandemic. |
| 82 | Rastogi, Chaturvedi, Sagar, Tandon, and Rastogi | 2022 | India | Cancer diagnosis | BD, ML | Classification of lung cancer |

pillars of future personalized healthcare. In particular, improved, powerful, and energy efficient smart sensors and devices will change the way we perceive personalized healthcare. Wireless body area networks, integrating nanoscale sensors and devices will be at the hearth of these technologies (Aceto et al., 2020). CC and FG technologies along with the developing 5G infrastructure will enable processing huge amount of data while bringing other issues such as security of devices, data privacy, and ethical issues to light. As we have remarked previously, these issues will require governmental regulation in the future.

Another foreseeable research point will be to provide the homogeneity of collected data. The BD is characterized by the volume, variety, and velocity of data. These properties inherently imply heterogeneity of health-related data in terms of format, sources, and attributes. Hence, advanced frameworks will be needed in the future to provide interoperability.

Finally, *anytime and anywhere connectivity* paradigm is evolving to *connectivity for anything* paradigm under the supervision of IoT. This evolution will ensure the availability of huge amount of data for eliciting meaningful information from it. Along with the prospective developments in the fields of DM and ML, it will be possible to exploit the large data and utilize it for all aspects of Healthcare 4.0 such as assisted living, rehabilitation, personalized healthcare, e-health systems, smart pharmaceuticals, and disease monitoring, etc. Examples of Industry 4.0 in other areas are as follows: risk assessment and management, concepts and theory of systems for improving company supply chain, cost efficiency of the 3D printing technology, process safety education of future employee, sustainable manufacturing such as the use of the robotic arm for digital manufacturing processes, evaluation for manufacturing enterprises, and so on.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of any affiliated organization or government.

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