eISSN 1983-9308

DATA ANALYSIS IN THE HEALTHCARE CONTEXT:

A SMART CITIES PERSPECTIVE

Versão do autor aceita publicada online: 18 nov. 2021
Publicado online: 23 nov. 2021

Como citar esse artigo - American Psychological Association (APA): Souza, F. F., Corsi, A., Sá, C. P., Pagani, R. N., Kovaleski, J. L. (2021). Data analysis in the healthcare context: a smart cities perspective. *Exacta*. DOI: https://doi.org/10.5585/exactaep.2021.20591.

Fabiane Florencio de Souza
fabianesouza@alunos.utfpr.edu.br
https://orcid.org/0000-0003-0415-590X
UTFPR
Msc. in Production Engineering, Federal University of Technology of Paraná. Undergraduate Degree in Production Engineering, State University of Paraná, Brazil.

Alana Corsi
alanacorsi@alunos.utfpr.edu.br
https://orcid.org/0000-0002-6319-8603
Federal University of Technology-Paraná (UTFPR)
Câmpus Ponta Grossa, Av. Monteiro Lobato, s/n-Km 04,
Ponta Grossa, PR 84016-210, Brazil
Msc. in Production Engineering, Federal University of Technology of Paraná. Undergraduate Degree in Production Engineering, State University of Paraná, Brazil.

Clayton Pereira de Sá
clayton.sa@ifpr.edu.br
Federal University of Technology-Paraná (UTFPR)
Câmpus Ponta Grossa, Av. Monteiro Lobato, s/n-Km 04,
Ponta Grossa, PR 84016-210, Brazil
Undergraduate Degree in Production Engineering, State University of Paraná, Brazil.

Regina Negri Pagani
reginapagani@utfpr.edu.br
https://orcid.org/0000-0002-2655-6424
Federal University of Technology-Paraná (UTFPR)
Câmpus Ponta Grossa, Av. Monteiro Lobato, s/n-Km 04,
Ponta Grossa, PR 84016-210, Brazil
Federal university of technology-Paraná - UTFPR
PhD in Production Engineering, Federal University of Technology of Paraná, and Sorbonne Universités. MSc in Production Engineering, Federal University of Technology of Paraná. Specialist in Industrial Management, Federal University of Technology of Paraná. Undergraduate Degree in Business Administration, State University of Maringá, Brazil.

João Luiz Kovaleski
kovaleski@utfpr.edu.br
Federal University of Technology-Paraná (UTFPR)

EXACTA Engenharia de Produção eISSN 1983-9308

Câmpus Ponta Grossa, Av. Monteiro Lobato, s/n-Km 04,
Ponta Grossa, PR 84016-210, Brazil
PhD in Industrial Instrumentation, University of Grenoble I. MSc in Industrial Informatics, Federal University of Technology of Paraná. MSc in Electronic Systems, Institut Polithnique de Grenoble. Undergraduate Degree in Electronic Industrial Engineering, Federal University of Technology of Paraná. Undergraduate Degree in Industrial Automation, University of Grenoble I, France.

Abstract

Cities are characterized as smart when they prioritize and develop ways to link technology, infrastructure, knowledge, and policies to improve the quality of life of citizens. In addition, technological application alone is not capable of making a city smart, people must be able to adapt and interact with technologies, as well as it is essential that the large volume of data generated by different devices, in real-time, called Big Data, are analyzed and interpreted, transforming them into interpretable information. In this context, this study aims to identify data analysis in the context of healthcare, as one of the domains of Smart Cities. For this, a bibliographic review was carried out, using the Methodi Ordinatio methodology, resulting in a portfolio of articles with scientific relevance, which was the source of data collection and analysis. Thus, the results obtained demonstrate that the most studied technologies in this context seek to analyze data with Big Data Analytics techniques, encompassing Artificial Intelligence and Machine Learning, which analyze data generated by "devices" in which Electronic Health Records are collected, and "sensors" often associated with the Internet of Things. However, some challenges were found, highlighting the need for data security and privacy, with Blockchain technology being mentioned several times as a possible solution, thus, by combining digital technologies and data analysis techniques, an approximation is obtained. real of smart city concept.

Keywords: Data Analysis. Big Data. Big Data Analysis. Healthcare. Health. Smart Cities. Technologies. Citizens. Machine Learning. Electronic Health.

Resumo

As cidades são caracterizadas como inteligentes quando priorizam e desenvolvem formas de relacionar tecnologia, infraestrutura, conhecimentos e políticas a fim de melhorar a qualidade de vida dos cidadãos. Além disso, somente a aplicação tecnológica não é capaz de tornar uma cidade inteligente, é necessário que as pessoas sejam capazes de adotar e interagir com as tecnologias, bem como, é imprescindível que o grande volume de dados gerados por diversos dispositivos, em tempo real, denominado de Big Data, sejam analisados e interpretados, transformando-os em informações interpretáveis. Nesse contexto, o presente estudo visa identificar o data analysis no contexto do healthcare, sendo um dos domínios das Smart Cities. Para isso, foi realizada uma revisão sistemática de literatura, por meio da metodologia Methodi Ordinatio, resultando em um portfólio de artigos com relevância científica, o qual foi fonte da coleta e análise de dados. Assim, os resultados obtidos demonstram que as tecnologias mais estudadas nesse contexto, buscam analisar os dados com técnicas de Big Data Analytics, englobando a Inteligência Artificial e Machine Learning, que analisam dados gerados por "devices" em que os Eletronic Health Records são coletados, e "sensors", muitas vezes associados a Internet of Things. Entretanto, alguns desafios foram encontrados, destacando-se a necessidade de segurança e privacidade de dados, sendo a tecnologia Blockchain mencionada várias vezes como uma solução possível, dessa forma, ao aliar tecnologias digitais e técnicas de análise de dados, obtém-se uma aproximação real do conceito de cidade inteligente.

Palavras-Chave: Data Analysis. Big Data. Big Data Analysis. Healthcare. Health. Smart Cities. Technologies. Cidadãos. Machine Learning. Electronic Health.

1 Introduction

The world is undergoing an intense technological revolution, directly affecting cities and the way they are organized. Thus, questions arise such as which advances allow to improve people's quality of life and how technology can collaborate in this process (UNESCO, 2011; Li et al., 2019).

In this article, the subjects Smart Cities, Big data, Data Analysis and Healthcare are addressed, highlighting some important elements to understand how Smart Cities are characterized and how they can face the different challenges to meet demographic changes, as well as the needs of citizens.

Discussions about what the cities of the future will be like are increasingly frequent and the literature has advanced on the subject, given a large number of publications in recent years (Bibri & Krogstie, 2017). In this context, it is important to identify how cities are characterized, and what requirements make them smart. It is considered a smart city, one that offers an adequate physical and technological infrastructure. However, the technological aspect is not enough to define a Smart City. Thus, cities can be characterized as intelligent when they prioritize and develop ways to relate technology, infrastructure, knowledge, development policies, and people.

The Smart Cities management process involves the use of data and information generated by users (Wu, 2020). With this, the citizens of these cities are benefited when there is a combination of physical and technological structures, public policies, as well as the offer of products and services by private companies, all connected in favor of meeting human needs.

It can be seen, therefore, that Smart Cities are great information generators, in a complex chain of technological infrastructure and algorithms, which use data and information that, when considered in the process of implementing public policies, translate into intelligent management of the various urban resources (König, 2021). In this scenario, it is essential that public managers and users, who use the data collected by the different mechanisms of capture, can interpret the information properly.

Big Data plays a fundamental role in capturing data, storing a large volume of elements resulting from interactions that take place in Smart Cities environments (Karimi et al., 2021). This process is essential to feed the system, generating information that helps decision-making and the implementation of actions to improve the services provided.

However, Big Data needs mechanisms that help its manipulation, management, and interpretation (Huang et al., 2021). The biggest challenge is not building technological structures and collecting data, but using it efficiently and effectively. This is where data analytics becomes essential. From the Big Data Analysis (BDA) it is possible to identify patterns of behavior, consumption, and other social habits, resulting in information that can be interpreted (Zeng et al., 2020).

In this process, the health sector is an important pillar to develop intelligent urban environments that are capable of improving people's quality of life. As noted in the literature, it is expected that in the coming years the elderly population will be larger (Pérez & Salvachúa, 2021). This significant portion of the global population will demand services in several areas, including the health area. Thus, planners and decision-makers in urban spaces need to consider these changes to propose strategies aimed at dealing with the new conditions of society.

Thus, it is observed that medical assistance and health care will have growing demand, putting pressure on the sectors involved to increase their capacity to adequately serve this population. Thus, BDA can be used to assist the implementation and administration of Healthcare.

In short, the health axis is a fundamental vector for the development of Smart Cities and presents a growing trend. Although several techniques and technologies allow keeping the

EXACTA Engenharia de Produção eISSN 1983-9308

database updated and with important information, contributing to decision making, strategies will be increasingly needed to deal with the amounts of data generated by different devices, to make the decision faster and more assertive decision-making, enabling the fulfillment of one of the Smart Cities objectives, which is to promote an improvement in the quality of life of citizens.

Therefore, implementing strategies that meet people's needs, involving citizens together with systems that constantly generate large amounts of data, resulting in more assertive public policies, translates into one of the challenges in the Smart Cities Healthcare sector.

Thus, to address or minimize the challenge addressed, this study aims to identify the technologies, techniques, and tools for Data Analysis, used in the context of Smart Cities, in the Healthcare area. The coordinated interaction between these technologies, techniques, and tools helps to manage the large volume of data, thus allowing them to be transformed into information that can be interpreted, making the decision-making process more assertive and with greater speed executed.

2 Theoretical Review

2.1 Smart Cities

With the increase in population and its concentration in urban areas, it became necessary to plan cities that allow meeting human needs and, at the same time, rationalize the use of natural resources. In the current scenario, the infrastructure of a city remains important, however, social expectations regarding cities have changed over time. Today, people are looking for quality of life, mobility, connectivity, information, and communication technologies that can make life easier in society, as well as performing tasks (Capdevila & Zarlenga, 2015).

It is in this context that the Smart Cities concept emerged, gaining more and more importance in the city planning process. For Neirotti et al. (2014), the main approaches to defining a Smart City are: how cities are guided to achieve their optimization goals, and their domains, which are considered important axes for the development of this model of cities. Literature characterizes Smart Cities by the wide use of Information and Communication Technology (ICT), as well as by the infrastructure offered by the city (Caragliu et al., 2013). For these authors, for a city to be intelligent, it is not enough to have only adequate infrastructure.

According to Caragliu et al. (2013), a city can be considered smart when there are investments that consider and involve the citizen in an interaction framework, in an interface

EXACTA Engenharia de Produção eISSN 1983-9308

capable of generating the well-being of society, as well as a planned infrastructure to drive sustainable growth. Thus, the objective of smart cities is to raise the quality of life of people, using technological solutions that reduce the impacts of human concentration, facilitating the daily lives of society.

For Neirotti et al. (2014), domains can influence the way Smart Cities develop. The authors identify how the classical literature approaches the domains, dividing them into two areas, namely: hard and soft. In the case of hard, consider the following factors: energy networks; Street lighting; natural resources and water; Waste Management; environment; transport, mobility, and logistics; office and residential buildings; medical care and public safety. About soft, they list the following factors: education and culture; social assistance and welfare; public administration and economy.

Thus, it is highlighted that it is not only ICTs that characterize the intelligence of cities, there must be environmental protection, optimization of economic resources, as well as policies that consider social factors in the process of developing cities (Caragliu et al., 2013). Therefore, technology is used to connect and integrate the various domains in urban regions, providing an interface between people, organizations, and public administration. In this sense, cities can be characterized as intelligent when they prioritize and develop ways to relate technology, infrastructure, knowledge, and policies that are capable of improving people's lives.

2.2 Data analysis

According to Manogaran and Lopez (2018), Big Data is a large volume of data from different sources, such as social networks, sensors, and other devices, which capture user data. These data sources can be classified as being heterogeneous, autonomous, and with distributed and decentralized controls (Wu et al., 2014; Zhang et al., 2014). On the other hand, Big Data can be classified as structured, semi-structured, and unstructured (Hu et al., 2014; Jee & Kim, 2013), is generated quickly and in large volumes. They are often scattered across the network and hardly ever integrated with real-time access.

It is necessary to highlight that Big Data needs tools that can process its data, generating information that can be interpreted. In this sense, Data Analysis techniques and technologies become fundamental, as they allow data and information to be interpreted and become relevant to users (Hu et al., 2014). In short, Data Analysis is a way to analyze and interpret data about a particular group.

For Sun et al. (2014), in the field of data management and information processing, many efforts have been undertaken. In the case of data collection, software and technologies are generally used to store the data, generating indicators that help in decision making, whether in the public or private sector. For Minelli et al. (2013), the development of less costly methods, which are reliable and useful for Big Data users, in the analysis processes, is essential. According to Davenport and Harris (2007), the private sector uses data analysis systems to generate insights for different areas of companies, being an important strategy for organizations to generate value through understanding and meeting the needs of customers. This same business concept becomes fundamental for the development of Smart Cities.

The structuring of data and information requires greater instrumentation, promoting the greater organization of information (Kauffmann et al., 2019). Chen et al. (2012) affirm that the themes of Business Intelligence and Big Data Analytics are associated. Thus, due to the similarity of concepts, it can be concluded that Data Analysis is a process of interpreting the data collected by the different interaction systems, being useful for the public and private sectors.

In this sense, Data Analytics represents the analysis of data captured in Big Data, which has been a recurrent theme in academic research around the world. The ability to capture, analyze and generate value from extracted data is increasingly valued in different sectors (Sanders, 2016). In short, Data Analysis is an important tool to develop and understand smart cities, as the data, when interpreted, helps to detect patterns about the analyzed public. Data Analysis allows public policymakers and companies to offer better services to society, as well as transform cities into smarter cities (Fox & Hendler, 2011). In this way, the indicators and information collected by Big Data can be interpreted in the Data Analysis process, improving the ability to understand the data and, consequently, on certain subjects.

According to Wasim et al. (2019), today's Big Data era is based on data processing; the application of information; Data Warehouse decision support models, data mining, and the Big Data era. Regarding Data Analysis, in general, it follows the following logical sequence: processing, organization, analysis, development of algorithms, observation, and decision-making. This process allows, after analyzing the data, the Data Analysis user can conclude on the subject under study and make better decisions. Smart Cities are beginning to take ownership of data analysis systems to improve the process of managing the interfaces between different technological systems.

The healthcare area has one of the largest data sets, as well as rapid growth in demand for these services (Kambatla et al., 2014). Thus, techniques and tools must be applied in this context, to turn a large amount of raw data into relevant information.

EXACTA Engenharia de Produção eISSN 1983-9308

According to Herland et al. (2014), in the field of healthcare, computational power has reached the ability to deal with Big Data through efficient algorithms, as well as with advances in hardware, allowing for the "mining" of data in large volumes, speed, variety, veracity and value of the data generated by Health Informatics. Therefore, to improve the Smart Cities management process, and specifically in the Healthcare field, public managers and users who use the data collected by the different collection mechanisms must be able to interpret the information properly. Thus, from Data Analysis it is possible to identify patterns of behavior, consumption, and other social habits.

2.3 Healthcare

With the aging of the population, the demand for health services tends to increase exponentially. According to the study, Global Health Care Outlook, laying the foundation for the future carried out by the English consulting company Deloitte, in 2020, it is estimated that the life expectancy of the world population should increase in the coming years. The study predicts that the average age will increase from 73.5 years in 2018 to 74.4 years in 2022. In this scenario, the number of people over 65 in the world will be approximately 12% of the global population. There will be almost 700 million people in this age group (Deloitte, 2020).

In Brazil, it is observed that, among the terms of social security, expressed in Article 194 of the Federal Constitution. 88, health is also a right of all citizens. Thus, Smart Cities need to be prepared for demographic changes, especially the aging process of the population. Thus, the planning of Smart Cities needs to consider the characteristics of the population. Health care services are aimed at people with poor health, requiring greater care and infrastructure of clinics, hospitals, home care, laboratories, as well as pharmacies, among others (Luongo et al, 2011; Cavallini & Bisson, 2010). In general, health services are based on the following processes (Mozachi & Souza, 2009; Cavallini & Bisson, 2010):

I. Administrative: human resources, data processing, finance, general services, safety, health, and occupational medicine, as well as the health sector supply chain, etc., and;
II. Technicians: nursing services, nutrition, and food, social assistance, data recording and files, statistics, diagnosis, treatment, various services, pharmacy services, etc.

In this scenario, services related to Healthcare must integrate with the concept of Smart Cities. The public and private health sectors need to develop actions to meet the growing demand and, at the same time, cities need to develop mechanisms to integrate this health care network. In addition, it is noteworthy that the healthcare field is increasingly gaining attention from public health policymakers, and for quality medical care, a public policy that requires constant changes to meet social needs is needed.

According to Chen et al. (2014), the field of health is one of the areas that can use Big Data to improve their management. In this context, it is possible to verify that the insertion of digital technologies in Smart Cities can improve operational aspects both in the infrastructure of cities and in the specific field of health. For Murdoch and Detsky (2013), the application of Big Data in Healthcare is inevitable, contributing to the quality and efficiency of services provided in the healthcare sector. Therefore, it is concluded that Data Analysis technologies in the field of Healthcare are necessary so that cities can properly handle the large amount of data generated by different sources, called Big Data, to turn data into information capable of being interpreted, adequately meeting the demand for health services more effectively.

3 Materials and Methods

To identify the technologies, techniques, and Data Analysis tools applied to Healthcare, in the context of Smart Cities, a bibliographic review will be carried out, using the Methodi Ordinatio methodology. For this, the nine protocols defined by Pagani et al. (2015; 2017) were adopted. So, initially (Steps 1 to 4), exploratory searches were carried out in different databases with several keywords. Since the Scopus database returned the largest number of articles among the databases tested, this one was selected to carry out the bibliographic review. Furthermore, from the exploratory searches, three combinations of keywords were defined. From the definition of the database and the combinations of keywords, the final search was performed, as shown in Table 1.

Table 1 – Combination of keywords and filtering procedures

Keyword Combination	Scopus
("health 4.0" OR "healthcare 4.0") AND "data analy*"	6
"health 4.0" OR "healthcare 4.0”	63
("health 4.0" OR "healthcare 4.0") AND "smart cit*"	2
Total	**71**
Filtering Procedures	**Deleted Articles**
Duplicate articles	8
Exclusion of articles outside the theme (title, abstract, and keywords)	40
Document Type	1
Total deleted articles	49
Numbers of articles in the portfolio	**22**

Source: Elaborated by the Authors (2020).

EXACTA Engenharia de Produção eISSN 1983-9308

After performing the definitive search in Scopus, the filtering procedures were started (Step 5). The purpose of these procedures is to eliminate duplicate articles, articles not related to the purpose of this study, and books, book chapters, and conference papers. The results obtained were, as shown in Table 1.

After the filtering procedures, the Impact Factor (IF) variables; Number of citations (Ci), and year of publication (PublishYear) were collected, and the InOrdinatio equation (1) was applied, Steps 6 and 7, ranking the articles in scientific relevance. The selected impact factor metric was Clarivate's Journal Citation Reports (JCR) 2020, the number of citations of the articles was collected in Google Scholar, and the year of publication of the articles was identified in the articles themselves. Thus, from the collection, Equation (1) InOrdinatio was applied.

$$\text{InOrdinatio} = (\text{IF}/1000) + \alpha*[10-(\text{ResearchYear}-\text{PublishYear})] + (\text{Ci}) \quad (1)$$

After sorting, a new filter was applied, eliminating articles that did not have JCR. Thus, six articles were deleted, resulting in a portfolio composed of 16 articles.

After defining the portfolio of scientific articles, these were located, starting the systematic reading of the articles (Steps 8 and 9), then allowing the procedures for data collection and analysis. For this, firstly, bibliometric analyzes were carried out in the portfolio, identifying the main authors of the portfolio, the topicality of the topic, the main keywords of the articles, as well as the main terms mentioned in the body of the articles. For this, NVivo 12 and VOSviewer software were used. Finally, the content analysis began, aiming to identify the Data Analysis techniques applied in the context of Healthcare in Smart Cities, thus fulfilling the objective of this research.

4 Results and Discussions

4.1 Bibliometric Analysis

The first bibliometric analysis performed was to identify the main authors of the portfolio. For this, the density map functionality of the VOSviewer software was used. The results obtained were, as shown in Figure 1.

EXACTA Engenharia de Produção eISSN 1983-9308

EXACTA Engenharia de Produção eISSN 1983-9308

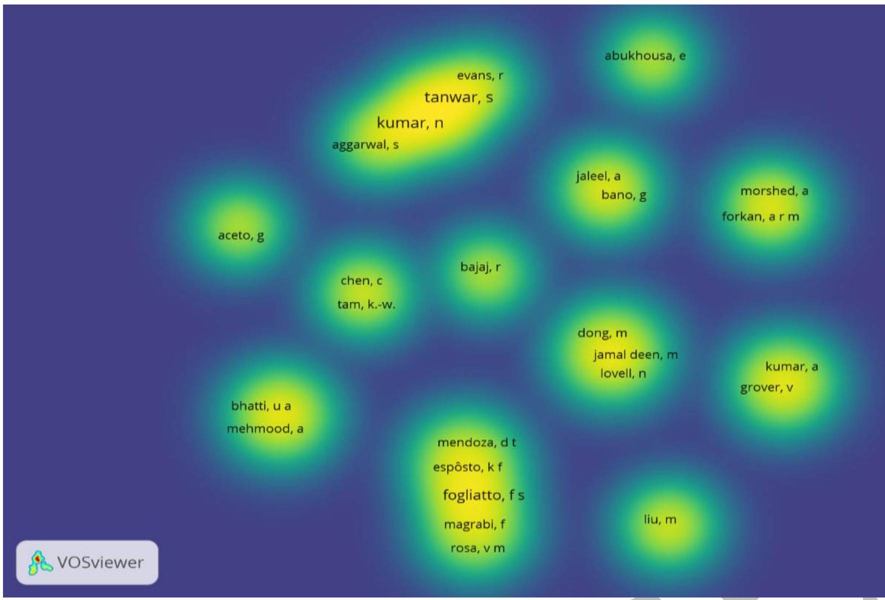

Figure 1 – Main authors
Source: Elaborated by the Authors (2020).

From the data generated in the software and from Figure 1, it is observed that there are 67 authors in the portfolio. Among these, the authors with the highest number of articles are Kumar, N. and Tanwar, S., with three articles each, and Fogliatto, F. S.; Tortorella, G.L.; and Tyagi, S., with two articles each. The other authors present one article each. Furthermore, it is observed that these main authors were networks of co-authorship among themselves, such as Kumar, Tyagi, and Tanwar, who have two articles in common, and Fogliatto and Tortorella have two articles in common. The second bibliometric analysis performed was to assess the topicality of the topic, as shown in Figure 2.

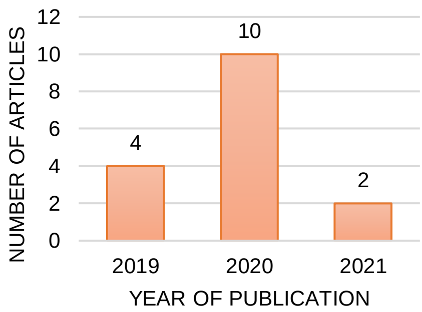

Figure 2 – Publication by year
Source: Elaborated by the Authors (2020).

Although the portfolio has presented some filtering procedures, these did not include exclusion filters by year of publication, therefore, it did not affect the visualization of the publication trend on the topic. Thus, it is observed that the topic has a considerable growth in publication, with a growth of about three times more articles from 2019 to 2020. As the research

Exacta – Engenharia de Produção
eISSN 1983-9308

was carried out based on articles published until March 2021, it is possible to have a vision that in the first quarter of the year there are already publications related to the topic.

Next, the main keywords of the portfolio were identified. For this, the Overlay Visualization of the VOSviewer software was used, allowing the identification of the actuality of the keywords, that is, the keywords mentioned in recently published articles, in older articles, and intermediate articles. The result obtained was, as shown in Figure 3.

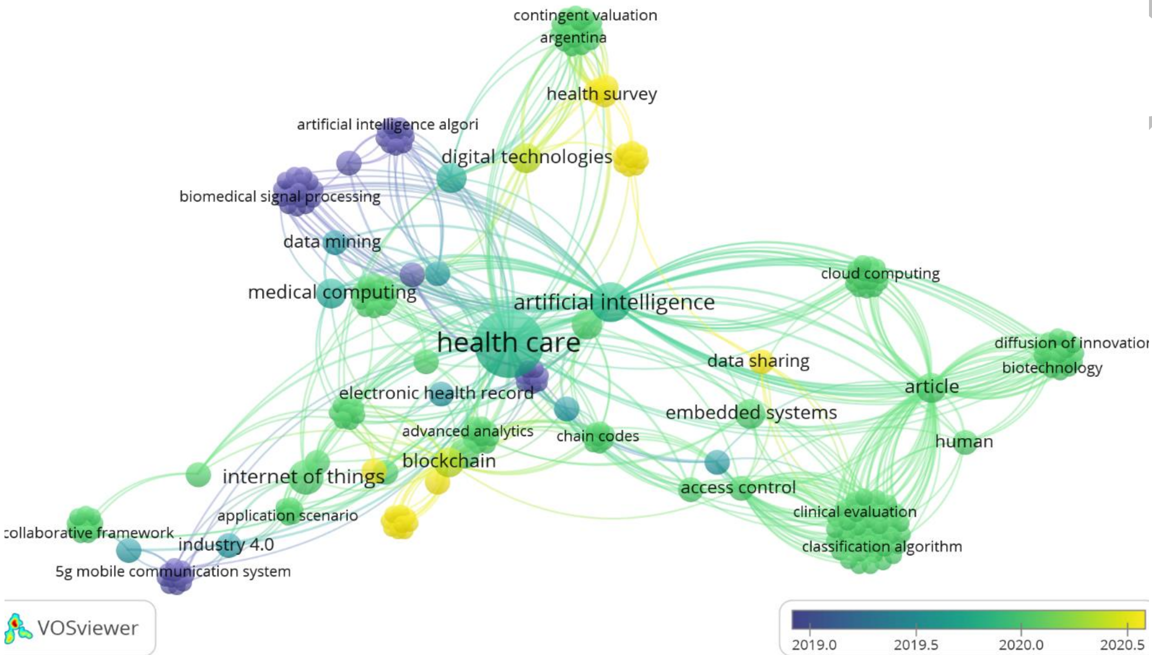

Figure 3 – Main keywords
Source: Elaborated by the Authors (2020).

From the data obtained in the software and from Figure 3, it is concluded that the portfolio has 246 keywords in total, with the main keywords most frequently mentioned being: "health care", mentioned in 15 portfolio articles, that is, 94% of the articles; “artificial intelligence”, mentioned in 5 articles; and “internet of things”, in 4 articles; “embedded systems”, “digital technologies”, “medical computing”, “security and privacy” and “blockchain”, mentioned in 3 articles each.

In addition to the most cited keywords, this software functionality allows you to identify the actuality of keywords. Thus, it is observed that the keywords mentioned in more recent articles, published after the second half of 2020 until today, are: “Health survey”; “data sharing”; “hospital sector”; “Internet of thing (IoT)” and “privacy by design”, mentioned in 2 articles each, followed by the keyword “blockchain”, mentioned in 3 articles. Next, the keywords mentioned in articles in intermediate years, between 2019 and 2020, are: “Health care” mentioned in 15 articles; “artificial intelligence”, mentioned in 5 articles; “Internet of things”, mentioned in 4 articles; “medical computing”, “security and privacy”, “health-care system", mentioned in 3 articles each; and "data mining"; "interoperability" and "access control", mentioned in 2 articles each. Finally, the oldest keywords, mentioned in articles published until 2019, are: "Diagnosis", mentioned in 3 articles; and "recommender Systems", mentioned in 2 articles. Finally, the main themes addressed throughout the articles were identified through the Word Cloud functionality of the NVivo 12 software, as shown in Figure 4.

Figure 4 – Portfolio cloud word
Source: Elaborated by the Authors (2020).

From Figure 4 and the data obtained with the automatic coding of the NVivo 12 software, it was identified that the main terms mentioned in the portfolio were "data", mentioned in the 16 articles and present in 309 excerpts; "system", present in the 16 articles and 240 excerpts; "health", present in 16 articles and mentioned in 200 excerpts; "healthcare", present in 13 articles and 154 excerpts; "devices", mentioned in 14 articles and 131 excerpts. In addition, from the automatic coding, the contexts in which the term "date" was used were identified, as shown in Figure 5.

EXACTA Engenharia de Produção eISSN 1983-9308

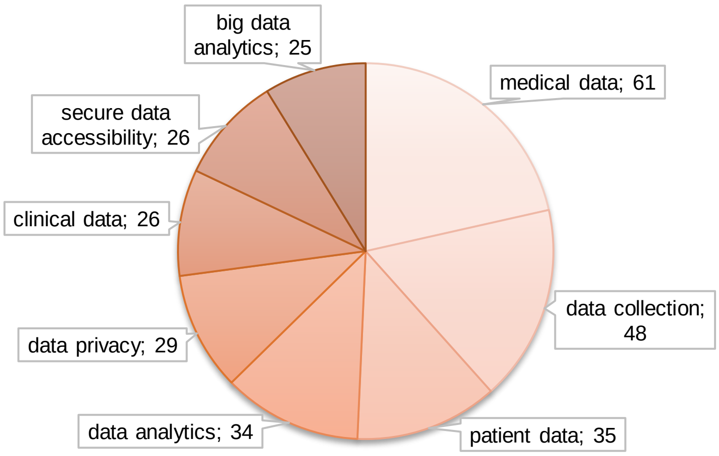

Figure 5 – Main words related to data
Source: Elaborated by the Authors (2020).

From this, it appears that "medical data" and "data collection" are the main terms mentioned when addressing the issue of data. In addition, some challenges related to Big Data Analytics were also recurrent, as the terms "data analytics", "data privacy", and "secure data accessibility". Finally, the main "devices", "sensors" and "technologies" mentioned in the portfolio were identified, as shown in Figure 6.

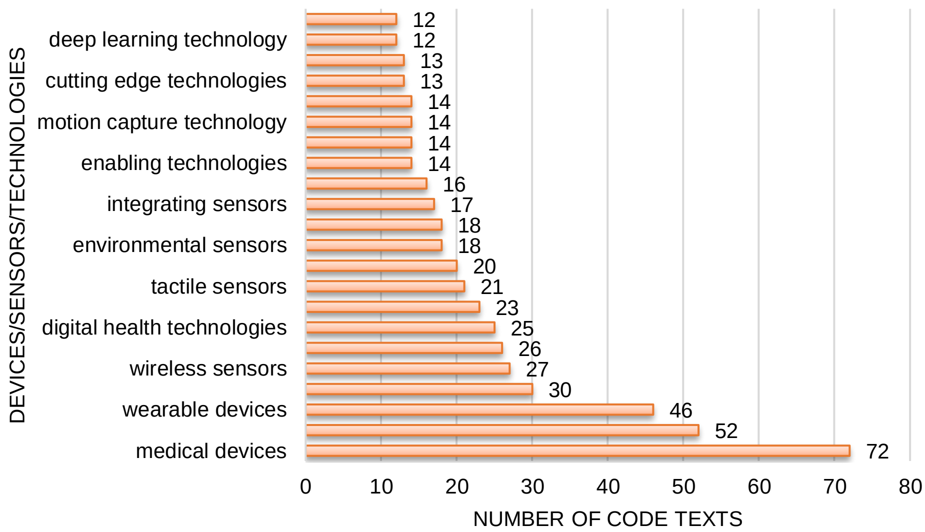

Figure 6 – Main devices, sensors, and technologies
Source: Elaborated by the Authors (2020).

Thus, there is a focus on "medical devices", "smart devices" and "wearable devices", but also on information and communication technologies being applied in the context of healthcare.

It is possible to observe the presence of "sensors" linked to different technologies, showing the adoption of Internet of Things (IoT) technologies, capable of capturing data in real-

EXACTA Engenharia de Produção eISSN 1983-9308

time, from "temperature sensors" and "body sensors network", which can be analyzed using Data Analysis techniques in the scenario, as presented in the next Section.

4.2 Content analysis

To identify Data Analysis technologies, techniques, and tools in the context of Healthcare in Smart Cities, a bibliographic review was carried out, using the Methodi Ordinatio, which resulted in a portfolio of articles with scientific relevance. From this portfolio, bibliometric and content analyzes were performed.

Thus, to achieve the objective of this research, the articles were read, and some aspects collected, such as the objectives of the articles, the technologies, techniques, and tools mentioned in the context of Healthcare, data sources, storage technologies, and manipulation of data, treatment areas, mentioned diseases, and, finally, challenges and benefits of the mentioned techniques.

Thus, it was possible to identify that the articles had objectives that aimed to understand several aspects, such as the evolution of technologies inserted in the health area (Chen et al., 2020), the barriers and impacts perceived in the adoption of these technologies (Tortorella et al., 2020; Tortorella et al., 2021), the characterization of the new phase of health, known as Health 4.0 (Jayaraman et al., 2019; Aceto et al., 2020), and the assessment of the impact of the 5G Internet and its contributions to the health area (Jayaraman et al., 2019).

But specifically, about Data Analysis, the articles addressed the need for integration and incorruptibility of access to patient data (Jaleel et al., 2020), with the use of Blockchain technology (Kumar et al., 2020), to make access to patient data is safer, with this theme being data security and patient privacy, the objective of a study by other authors such as Qiu et al. (2020), Tanwar et al. (2020) and Aggarwal et al. (2021).

The adoption of medical recommendation systems (Bhatti et al., 2018; Sharma et al., 2019) and the use of robots in the construction of a Cyber-Physical System (CPS) based on Data Analysis (Yang et al., 2020), was also explored.

Finally, Al-Jaroodi et al. (2020) addressed the relationship between technologies inserted in the health area, with efficiency and cost reduction.

Based on the objectives identified in the articles, it is also possible to observe some data sources, especially the Electronic Health Records (EHRs), also known as Electronic Medical Records (EMR) (Hung et al., 2019; McCarthy et al., 2020) or Personal Healthcare Records (PHR) (Koumaditis & Hussain, 2018) and Internet of Things (IoT) related sensors. Figure 7 presents a compilation of the data sources and databases mentioned in the articles.

eISSN 1983-9308

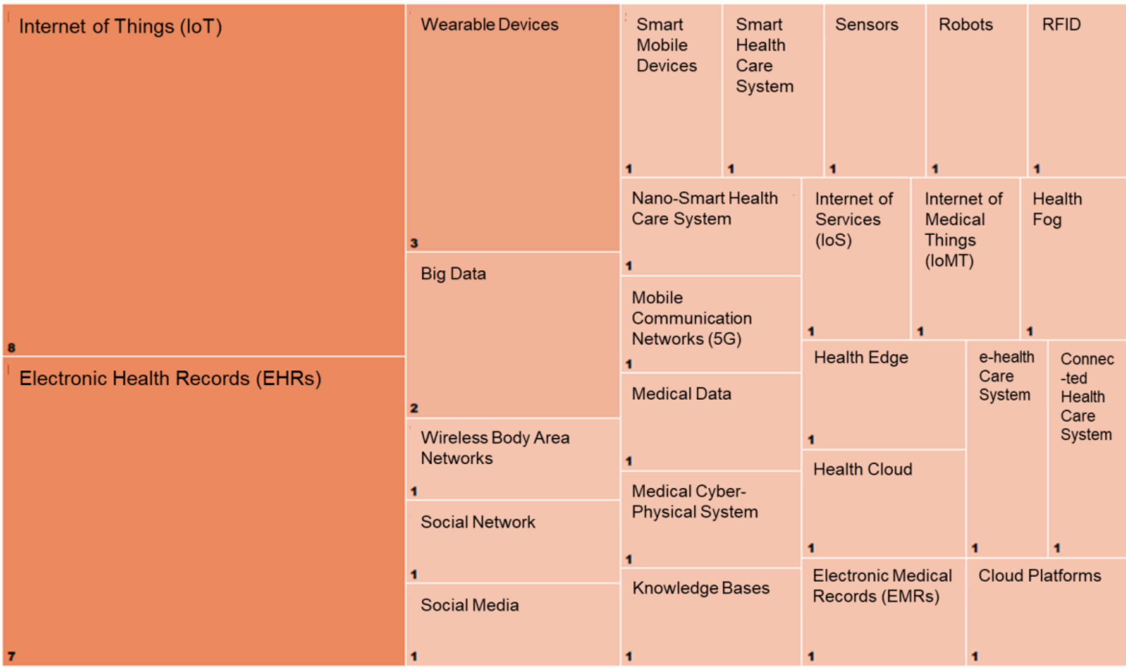

Figure 7 – Sources and databases in the healthcare context
Source: Elaborated by the Authors (2020).

As seen in Figure 7, the data come from different sources, and, therefore, can present different formats, such as numbers, texts, audios, images, and others. For this data to be transformed into useful information for medical decision-making, it is necessary to know what are the techniques, technologies, and appropriate tools to analyze this data, which takes place in different stages, and Table 2 gathers some of these methods according to the portfolio of articles, focusing on the data manipulation and storage step.

Table 2 – Tools, technologies, and techniques to manipulate and store health data

Article	Tools, technologies, and techniques
Tanwar et al. (2020)	Blockchain.
Aceto et al. (2020)	Cloud Computing; Fog Computing.
Yang et al. (2020)	Cloud Computing.
Aggarwal et al. (2021)	Blockchain.
Chen et al. (2020)	Cloud Computing; Fog Computing.
Jaleel et al. (2020)	Edge computing.
Bhatti et al. (2018)	Apache Hadoop MapReduce.
Al-Jaroodi et al. (2020)	Blockchain.
Sharma et al. (2019)	Edge Computing; Fog Computing; Cyber-physical system.

Source: Elaborated by the Authors (2020).

EXACTA Engenharia de Produção eISSN 1983-9308

Blockchain technology is mentioned in three articles, and its main relationship with Data Analysis is closely related to ensuring data security and privacy (Tanwar et al., 2020), a very important issue when it comes to patient data, which is personal information, and therefore sensitive.

This data can be stored on several servers around the world, this type of storage became known as cloud storage, highlighting the technologies of Cloud Computing and Fog Computing to perform this task (Aceto et al. 2020; Chen et al. 2020). The Edge Computing technique is used to store data so that it can be accessed quickly (Sharma, Singh & Bajaj, 2019), using less than the internet's update rate.

Apache Hadoop MapReduce stands out in this context for processing large amounts of data, through a technique that divides a set of data into independent blocks to be processed in parallel (Mohamed et al., 2019).

In the context of health, when building an environment based on software with mechanical and electronic parts, there is the Cyber-Physical System, which consists of the control and monitoring of data transfer in real-time, through the internet (Sharma, Singh & Bajaj, 2019).

All of these technologies and techniques can be combined and used to manipulate and store health data from different patients and health organizations, making it possible to analyze this data through other technologies, as shown in Table 3.

Table 3 – Combination of technologies and techniques to manipulate and store health data

Article	Technologies and techniques
Tanwar et al. (2020)	Data Analytics Algorithm
Aceto et al. (2020)	Machine Learning; Big Data Analysis; Genomic Analysis.
Hathaliya et al. (2019)	AVISPA tool.
Gupta et al. (2019)	Statistical Analysis.
Jayaraman et al. (2019)	Artificial Intelligence; Data mining; Machine Learning; Pattern Recognition; Natural Language Processing (NLP); Deep Learning; Semantic reasoning; Image Processing; Computer vision.
Qiu et al. (2020) and Dashtban and Li (2021)	Encryption algorithms; Deep Learning; Statistical Analysis.
Tortorella et al. (2020)	ANOVA; MANOVA (Multivariate Analysis of Variance);
Yang et al. (2020)	Big data analysis; Artificial Intelligence; Deep Learning; Artificial Neural Network; Natural Language Processing; Computer Vision.
Aggarwal et al. (2021)	Big Data analysis; Artificial Intelligence.
Tortorella et al. (2021)	Statistical Analysis;
Chen et al. (2020)	Artificial Intelligence;
Bhatti et al. (2018)	Algorithm fb-kNN; Data Mining.
Al-Jaroodi et al. (2020)	Big Data Analytics;
Sharma et al. (2019)	Big Data Analysis; Artificial intelligence; Machine Learning; Advanced network technologies.

EXACTA Engenharia de Produção eISSN 1983-9308

Source: Elaborated by the Authors (2020).

In the analysis of health data, the Big Data Analysis, which encompasses Machine Learning and Artificial Intelligence (Sharma et al., 2019), stands out. Big Data Analysis brings together several technologies, techniques, and tools capable of working with Big Data, with Machine Learning being an important part of learning patterns related to this data, which allows Artificial Intelligence to develop based on these learnings and assume a disease prediction approach or medication recommendation in the healthcare environment.

Other techniques such as Statistical Analysis and Data Mining were also cited as a way to extract relevant information from health data, so a combination of different technologies may be performed to optimize Data Analysis.

The proper use of these tools in the healthcare context can result in many advantages for healthcare organizations and patients. Table 4 highlights some of the benefits mentioned by the authors.

Table 4 – Combination of technologies and techniques to manipulate and store health data

Article	Benefits
Kumar et al. (2020); Tanwar et al. (2020); Aggarwal et al. (2021)	Blockchain can increase efficiency and security in analyzing patient data, enable uninterrupted access to data in healthcare databases, and consequently improve the structure of healthcare services. The information that is stored through Blockchain technology, meaning these public or private data, will be available anywhere and at any time, in a distributed and decentralized manner.
Jayaraman et al. (2019); Al-Jaroodi et al. (2020)	The goals of Healthcare 4.0 are to provide quality healthcare services to patients, increasing the efficiency of resource utilization and operations. The interdisciplinarity of Healthcare 4.0 will allow technologies to address social and human aspects in the available data, increasing the quality of healthcare.
Jaleel et al. (2020)	The possibility of having Data Interoperability (Jaleel et al. 2020) through storage technologies is a great benefit for Data Analysis.
Tortorella et al., 2021	Technologies can reduce over-reliance on human skills (Tortorella et al. 2021), and promote a less stressful work environment due to reduced workload.
Hathaliya et al. (2019)	Authentication through patient biometrics can make data access more secure and reliable, and less susceptible to attacks and data theft.
Aceto et al. (2020)	Data Analysis technologies make it possible to gain new insights and access actionable information based on health data.
Qiu et al. (2020); Yang et al. (2020); Gomes et al. (2021)	The implementation of advanced algorithms, combined with other Big Data Analysis techniques, can prevent data from being susceptible to attacks, in addition to being of great benefit to integrate, analyze and manage data.
Yang et al. (2020)	The integration between Artificial Intelligence, Deep Learning, Artificial Neural networks, Natural Language Processing, and Computer Vision can increase the quality of medical treatments. And with the help of Big Data Analysis, building an intelligent, shared database would make it possible to provide medical decision support.
Kumar et al. (2020)	The Internet of Things (IoT) can generate automatic alerts when equipment failures occur or even identify fluctuations in the patient's health status.
Chen et al. (2020)	Artificial Intelligence is a strong ally in prioritizing activities to be performed regarding the patient's health.
Bhatti et al. (2018)	Improved medical performance, reduced mortality rate, assertiveness in prescribing medications, and more accurate diagnoses are some of the

	benefits obtained with the use of Data Analysis techniques in the health context.

Source: Elaborated by the Authors (2020).

The benefits are mainly focused on ensuring the security and privacy of patient data, in addition to increasing the efficiency of the use of resources by health organizations, also contributing to monitoring and assertiveness in the recommendation of medications and treatments for the patient's health.

Despite the variety of resources capable of achieving the ultimate goal of Data Analysis, which is to extract information from a large amount of different data, there are still challenges to be overcome.

In the Healthcare environment, demands related to the security and privacy of patient data were mentioned, among other issues, as shown in Table 5, which can be considered an agenda for future research on the subject.

Table 5 – Challenges in data health

Article	Challenge
Aceto et al. (2020); Jayaraman et al. (2019)	Difficulty analyzing heterogeneous data from Big Data.
Aggarwal et al. (2021); Hathaliya et al. (2019); Kumar et al., (2020); Qiu et al. (2020); Sharma et al. (2019)	Need to ensure the security of patient data, protecting their privacy.
Tanwar et al. (2020); Tortorella et al. (2021); Sharma et al. (2019)	Urgency in reducing health-related costs through Technologies.
Al-Jaroodi et al. (2020)	Due to the diversity of technologies, tools, and techniques, it is difficult to choose the best one for each objective in the health area.
Jaleel et al. (2020); Jayaraman et al. (2019)	Extract information from large amounts of data in real-time.
Bhatti et al. (2018)	Lack of professionals with sufficient interdisciplinary knowledge to analyze health data.
Bhatti et al. (2018)	Need for greater efficiency in disease prediction based on available data.
Hathaliya et al. (2019)	Self Health Big Data Storage Cost.
Sharma et al. (2019)	Need to change the mindset of health professionals for greater acceptance of technologies and new forms of analysis.

Source: Elaborated by the Authors (2020).

Although the privacy and security of patient data have been mentioned as one of the benefits of using technologies for Data Analysis in healthcare, this is also a critical point about the challenges to be faced.

Issues such as the cost of storage of healthcare Big Data and greater knowledge regarding the use of available technologies for Data Analysis were highlighted by the authors, highlighting the need for research that further explores the available technologies, as proposed in the purpose of this article.

Therefore, there is a vast field of study for researchers and professionals in the field of health and technology, regarding the application of these technologies in practice in health organizations.

When addressing this issue, some steps are taken so that Healthcare can follow the technological developments proposed by the concept of Smart Cities. Thus, it is concluded that Data Analysis technologies are necessary for the context of Smart Cities, as well as in the specific field of Healthcare, allowing to deal with a large amount of data, in real-time and in a heterogeneous way.

It is also concluded that the application of technologies alone is not capable of making a city smart, especially if the data generated and collected cannot be grouped and transformed into relevant and interpretable information, allowing decisions to be taken based on data. Thus, when digital technologies are combined with data analysis techniques, with a focus on meeting the needs of citizens, there is a real approximation of the concept of a smart city.

5 Conclusion

Given the increasing availability of data in the health sector, being generated by different sources and in an increasingly shorter period, it is necessary to envision the options available to extract important information from these data, to improve various aspects of patient follow-up. Thus, this article sought to identify the technologies, techniques, and tools for Data Analysis, which lead to the development of Smart Cities in the Healthcare area.

Electronic Health Records (EHRs) and Internet of Things (IoT) sensors stood out as sources of data in the health context. Blockchain technology highlights the need to ensure data security, while the most cited Big Data Analysis techniques encompass Machine Learning and Artificial Intelligence to promote the efficiency of Data Analysis.

By bringing together the technologies, techniques, and tools available in the current literature, this research presented as a limitation the lack of a practical view of their application. Therefore, future research can focus on seeking practical applications of the technologies listed in this article, in addition to exploring the challenges mentioned in Table 5.

REFERENCES

Aceto G, Persico V, Pescapé A. *Industry 4.0 and Health: Internet of Things, Big Data, and Cloud Computing for Healthcare 4.0.* Journal of Industrial Information Integration, 18, 100129, 2020. https://doi.org/10.1016/J.JII.2020.100129

Aggarwal S, Kumar N, Alhussein M, Muhammad G. *Blockchain-Based UAV Path Planning for Healthcare 4.0: Current Challenges and the Way Ahead*. IEEE Network, 35(1), 20–29, 2021. https://doi.org/10.1109/MNET.011.2000069

Al-Jaroodi J, Mohamed N, AbuKhousa E. *Health 4.0: On the Way to Realizing the Healthcare of the Future*. IEEE Access, 2020. https://doi.org/10.1109/ACCESS.2020.3038858

Bhatti UA, Huang M, Wu D, Zhang Y, Mehmood A, Han H. *Recommendation system using feature extraction and pattern recognition in clinical care systems*. Enterprise Information Systems: 13(3), 329–351, 2018. https://doi.org/10.1080/17517575.2018.1557256

Bibri S, Krogstie J. *Smart sustainable cities of the future: An extensive interdisciplinary literature review.* Sustainable Cities and Society, 31, 183-212, 2017. https://doi.org/10.1016/j.scs.2017.02.016

Capdevila I, Zarlenga M. *Smart City or Smart Citizens? The Barcelona Case.* SSRN Electronic Journal, 2015. https://doi.org/10.2139/SSRN.2585682

Caragliu A, Del Bo C, Nijkamp P. *Smart Cities in Europe*. Routledge, 185-207, 2013.

Cavallini ME, Bisson MP. (2002). *Farmácia hospitalar: um enfoque em sistemas de saúde*. Manole.

Chen C, Loh E-W, Kuo KN, Tam K-W. *The Times they Are a-Changin' – Healthcare 4.0 Is Coming!* Journal of Medical Systems, 44(2), 1–4, 2019. https://doi.org/10.1007/S10916-019-1513-0

Chen H, Chiang RHL, Storey VC. *Business intelligence and analytics: From big data to big impact.* MIS Quarterly: Management Information Systems, 36(4), 1165–1188, 2012. https://doi.org/10.2307/41703503

Chen M, Mao S, Liu Y. *Big Data: A Survey*. Mobile Networks and Applications, 19(2), 171–209, 2014. https://doi.org/10.1007/S11036-013-0489-0

Dashtban M, Li W. *Predicting non-attendance in hospital outpatient appointments using deep learning approach*. Health Systems, 1-22, 2021 https://doi.org/10.1080/20476965.2021.1924085

Davenport TH, Harris JG. *Competição analítica: vencendo através da nova ciência.* Alta Books, 2020.

Deloitte (2020). *2020 global health care outlook: Laying a foundation for the future*. [online] Available at: <https://www2.deloitte.com/content/dam/Deloitte/br/Documents/life-sciences-health-care/Deloitte-2020-global-health-care-outlook.pdf> [Accessed 27 May 2021].

Fox P, Hendler J. *Changing the Equation on Scientific Data Visualization*. Science, 331(6018), 705–708, 2011. https://doi.org/10.1126/SCIENCE.1197654

Gomes MAS, Silva VL, Kovaleski JL, Pagani RN. *Big data analytics applied to health services: a literature review.* Exacta, 0(0), 2021. https://doi.org/10.5585/EXACTAEP.2021.17297

Gupta R, Tanwar S, Tyagi S, Kumar N. *Tactile internet and its applications in 5G era: A comprehensive review.* International Journal of Communication Systems, 32(14), e3981, 2019. https://doi.org/10.1002/DAC.3981

Hathaliya JJ, Tanwar S, Tyagi S, Kumar N. *Securing electronics healthcare records in Healthcare 4.0 : A biometric-based approach.* Computers & Electrical Engineering, 76, 398–410, 2019. https://doi.org/10.1016/J.COMPELECENG.2019.04.017

Herland M, Khoshgoftaar TM, Wald R. *A review of data mining using big data in health informatics.* Journal Of Big Data, 1(1), 1–35, 2014. https://doi.org/10.1186/2196-1115-1-2

Huang H, Yao X, Krisp J, Jiang B. *Analytics of location-based big data for smart cities: Opportunities, challenges, and future directions*. Computers, Environment And Urban Systems, 90, 101712, 2021. https://doi.org/10.1016/j.compenvurbsys.2021.101712

Hu H, Wen Y, Chua TS, Li X. *Toward scalable systems for big data analytics: A technology tutorial.* IEEE Access, 2, 652–687, 2014. https://doi.org/10.1109/ACCESS.2014.2332453

Hung SY, Nakayama M, Chen CC, Tsai FL. *Physician perceptions of electronic medical records: The impact of system service quality, and generation/experience gaps.* International Journal of Healthcare Technology and Management, 17(4), 229–254, 2019. https://doi.org/10.1504/IJHTM.2019.104936

Jaleel A, Mahmood T, Hassan MA, Bano G, Khurshid SK. *Towards Medical Data Interoperability through Collaboration of Healthcare Devices.* IEEE Access, 8, 132302–132319, 2020. https://doi.org/10.1109/ACCESS.2020.3009783

Jayaraman PP, Forkan ARM, Morshed A, Haghighi PD, Kang Y-B. *Healthcare 4.0: A review of frontiers in digital health.* Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(2), e1350, 2020. https://doi.org/10.1002/WIDM.1350

Jee K, Kim GH. *Potentiality of big data in the medical sector: focus on how to reshape the healthcare system.* Healthcare Informatics Research, 19(2), 79–85, 2013. https://doi.org/10.4258/HIR.2013.19.2.79

Kambatla K, Kollias G, Kumar V, Grama A. *Trends in big data analytics*. Journal of Parallel and Distributed Computing, 74(7), 2561–2573, 2014. https://doi.org/10.1016/J.JPDC.2014.01.003

Karimi Y, Haghi Kashani M, Akbari M, Mahdipour E. *Leveraging big data in smart cities: A systematic review.* Concurrency And Computation: Practice And Experience, 33(21), 2021. https://doi.org/10.1002/cpe.6379

Kauffmann E, Peral J, Gil D, Ferrández A, Sellers R, Mora H. *A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake* *review detection for marketing decision-making*. Industrial Marketing Management, 90, 523–537, 2020. https://doi.org/10.1016/J.INDMARMAN.2019.08.003

König P. *Citizen-centered data governance in the smart city: From ethics to accountability*. Sustainable Cities And Society, 75, 103308, 2021. https://doi.org/10.1016/j.scs.2021.103308

Koumaditis K, Hussain T. *Personal healthcare records research: past, present and new dimensions*. International Journal of Healthcare Technology and Management, 17(1), 1–28, 2018. https://doi.org/10.1504/IJHTM.2018.091821

Kumar A, Krishnamurthi R, Nayyar A, Sharma K, Grover V, Hossain E. *A Novel Smart Healthcare Design, Simulation, and Implementation Using Healthcare 4.0 Processes*. IEEE Access, 8, 118433–118471, 2020. https://doi.org/10.1109/ACCESS.2020.3004790

Li X, Fong PSW, Dai S, Li Y. *Towards sustainable Smart Cities: An empirical comparative assessment and development pattern optimization in China*. Journal of Cleaner Production, 215, 730-743, 2019.

Luongo J, Rocha RM, Miranda TVM, Hervás MJW, Silva RMA. Gestão de qualidade em saúde. São Paulo: Rideel, 239-65, 2011.

Manogaran G, Lopez D. *Spatial cumulative sum algorithm with big data analytics for climate change detection*. Computers & Electrical Engineering, 65, 207–221, 2018. https://doi.org/10.1016/J.COMPELECENG.2017.04.006

McCarthy S, Fitzgerald C, Sahm L, Bradley C, Walsh EK. *Patient-held health IT adoption across the primary-secondary care interface: a Normalisation Process Theory perspective*. Health Systems, 1-13, 2020. https://doi.org/10.1080/20476965.2020.1822146

Minelli M, Chambers M, Dhiraj A. *Big data, big analytics: emerging business intelligence and analytic trends for today's businesses*. John Wiley & Sons, 578, 2013.

Mozachi N, Souza VHSD. O hospital: manual do ambiente hospitalar. Curitiba: Manual Real, 2005.

Mohamed A, Najafabadi MK, Wah YB, Zaman EAK, Maskat R. *The state of the art and taxonomy of big data analytics: view from new big data framework.* Artificial Intelligence Review, 53(2), 989–1037, 2019. https://doi.org/10.1007/S10462-019-09685-9

Murdoch T, Detsky A. *The Inevitable Application of Big Data to Health Care*. JAMA, 309(13), 1351, 2013.

Neirotti P, De Marco A, Cagliano AC, Mangano G, Scorrano F. *Current trends in Smart City initiatives: Some stylised facts.* Cities, 38, 25–36, 2014. https://doi.org/10.1016/J.CITIES.2013.12.010

Pagani RN, Kovaleski JL, Resende LM. *TICs na composição da Methodi Ordinatio: construção de portfólio bibliográfico sobre Modelos de Transferência de Tecnologia*. Ciência Da Informação, 24(2), 161–187, 2018. https://doi.org/10.18225/CI.INF..V47I1.1886

Pérez L, Salvachúa J. *An Approach to Build e-Health IoT Reactive Multi-Services Based on Technologies around Cloud Computing for Elderly Care in Smart City Homes*. Applied Sciences, 11(11), 5172, 2021. https://doi.org/10.3390/app11115172

Qiu H, Qiu M, Liu M, Memmi G. *Secure Health Data Sharing for Medical Cyber-Physical Systems for the Healthcare 4.0.* IEEE Journal of Biomedical and Health Informatics, 24(9), 2499–2505, 2020. https://doi.org/10.1109/JBHI.2020.2973467

Sanders NR. *How to Use Big Data to Drive Your Supply Chain*. California Management Review, 58(3), 26-48, 2016. https://doi.org/10.1525/CMR.2016.58.3.26

Sharma D, Singh GA, Bajaj R. *Evolution from ancient medication to human-centered Healthcare 4.0: A review on health care recommender systems*. International Journal of Communication Systems, e4058, 2019. https://doi.org/10.1002/DAC.4058

Sun Y, Yan H, Lu C, Bie R, Zhou Z. *Constructing the Web of Events from Raw Data in the Web of Things.* Mobile Information Systems, 10(1), 105–125, 2014. https://doi.org/10.1155/2014/517486

Tortorella GL, Fogliatto FS, Espôsto KF, Vergara AMC, Vassolo R, Mendoza DT, Narayanamurthy G. *Effects of contingencies on healthcare 4.0 technologies adoption and barriers in emerging economies.* Technological Forecasting and Social Change, 156, 2020. https://doi.org/10.1016/J.TECHFORE.2020.120048

Tortorella GL, Saurin TA, Fogliatto FS, Rosa VM, Tonetto LM, Magrabi F. *Impacts of Healthcare 4.0 digital technologies on the resilience of hospitals*. Technological Forecasting and Social Change, 166, 120666, 2021. https://doi.org/10.1016/J.TECHFORE.2021.120666

UNESCO (United Nations Educational, Scientific and Cultural Organization). From green economies to green societies: UNESCO's commitment to sustainable development, 2011. Disponível em: http://unesdoc.unesco.org/images/0021/002133/213311e.pdf. Acesso em: 03 Nov. 2021.

Wasim A, Varalakshmi M, Sudeepthi J. *Streaming Big Data Analytics- Current Status, Challenges and Connection of unbounded data Processing platforms.* International Journal of Innovative Technology and Exploring Engineering, 8(9S2), 698-700, 2019.

Wu W. *Determinants of citizen-generated data in a smart city: Analysis of 311 system user behavior.* Sustainable Cities And Society, 59, 102167, 2020. https://doi.org/10.1016/j.scs.2020.102167

Wu X, Zhu X, Wu GQ, Ding W. *Data mining with big data*. IEEE Transactions on Knowledge and Data Engineering, 26(1), 97–107, 2014. https://doi.org/10.1109/TKDE.2013.109

Yang G, Pang Z, Jamal Deen M, Dong M, Zhang YT, Lovell N, Rahmani AM. *Homecare Robotic Systems for Healthcare 4.0: Visions and Enabling Technologies.* IEEE Journal of Biomedical and Health Informatics, 24(9), 2535–2549, 2020. https://doi.org/10.1109/JBHI.2020.2990529

EXACTA Engenharia de Produção eISSN 1983-9308

Zeng D, Tim Y, Yu J, Liu W. *Actualizing big data analytics for smart cities: A cascading affordance study*. International Journal Of Information Management, 54, 102156, 2020. https://doi.org/10.1016/j.ijinfomgt.2020.102156

Zhang X, Yang LT, Liu C, Chen J. *A scalable two-phase top-down specialization approach for data anonymization using mapreduce on cloud*. IEEE Transactions on Parallel and Distributed Systems, 25(2), 363–373, 2014. https://doi.org/10.1109/TPDS.2013.48