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A LITERATURE ANALYSIS AND SUGGESTED RESEARCH AGENDA FOR HEALTHCARE

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Abstract
By describing how earlier studies have used big data, artificial intelligence, and machine learning to detect, treat, or solve healthcare problems, this study responds to the pressing need for research in healthcare analytics. In order to review the literature, pinpoint research gaps, and suggest a research agenda for scholars, academic institutions, and governmental healthcare organizations, healthcare science approaches are mixed with modern data science tools. The study adds to the body of literature by offering a cutting-edge analysis of healthcare analytics and by suggesting a path for future research to increase our understanding of the field. Researchers in the fields of data science and healthcare science, as well as practitioners, may find value in the findings of this study.

Keywords Healthcare, artificial intelligence, data analytics, big data, machine learning, and literature review

1.Introduction
The social, economic, and cultural facets of human existence are now deeply entwined with the swift advancement of novel technologies. This has had a major impact on a number of different fields and businesses, including medicine The use of wearable technology and Internet of Things (IoT) sensors, telemedicine, computing via the cloud, artificial intelligence (AI) healthcare solutions, and other practices are a few examples of these trends. A growing number of real-world applications and services are utilizing data science (DS). It uses many approaches on a broad spectrum of data to achieve various goals. Examples of techniques and technologies used in data science (DS) include machine learning (ML), databases, high-performance computing, cloud computing, data analytics (DA), machine learning (ML), mathematical and statistical modeling, and visualization.
Although a great deal of research has been done on the relationship between healthcare science and data analytics, very little has been done to determine how and to what extent big data analytics (BDA) can help the healthcare industry address current issues that data science can help identify and resolve In light of this, the purpose of this work is to delve further into the use of BD and DA algorithms to recognize and resolve healthcare issues.

2.Method
We used Webster and Watson's (2002) concept-centric literature review approach to address the research's goal. This method is in contrast to the author's centric approach, where readers are typically already familiar with the main topic and there are already studies that go into great detail about it. We selected the concept-centric approach because it facilitates a methodical synthesis of the literature and enables us to classify the literature on healthcare analytics in an initial manner. A thorough manual search was carried out throughout the main scholarly journals in the field of healthcare analytics during

the initial phase of the literature review. Thirteen articles were found in the exploratory search. After that, we perused the information in each of these journals
The next step was to use the "search terms" for literature searches to run searches using a carefully selected set of keywords in a number of well-known databases, such as Scopus, Web of Science, EBSCO, PubMed, and MEDLINE. For this literature review, the following keywords were used: IoT, big data, analytics, healthcare, and artificial intelligence. As a "search term," any meaningful combinations of these keywords were accepted. Healthcare analytics, large-scale data for healthcare, AI and healthcare, AI for medical purposes, and IoT in healthcare analytics are a few examples of search terms that were used. In addition, other search strategies were used, such as sensible keyword combinations like "healthcare"and "IoT" and "analytics," "big data" and "healthcare," "healthcare" and"AI," and so on.

3.Theoretical background

These days, DS—which uses algorithms operating on top of BD after a process—is being used by many disciplines to extract knowledge and insights from structured and unstructured data, with the goal of using innovative technologies to address traditional problems, like healthcare. In order to use BD, DS, AI, ML, and IoT as a lens through which to review the recent advancements in healthcare that have led to the creation of what is known as healthcare analytics, we provide theoretical background on these topics in this section. In order to work in a contextual domain of expertise, analytics is a multidisciplinary field that pulls from a wide range of skills and knowledge from multiple areas, including BD, DS, AI, ML, and IoT.

3.1 Big Data

These days, it is difficult to open a widely read publication—online or offline—without coming across a mention of DS, analytics, BD, or a combination of these (Agarwal and Dhar, 2014). Big Data requires the use of technical structures, analytics, and tools to extract insights that reveal hidden information and add value for businesses because it is so large, dispersed, diverse, and velocity. Three fundamental characteristics of BD are volume, velocity, and variety (also known as the three Vs). The main characteristic of BD is volume, which denotes its vastness and size (Lau et al., 2016). The rate at which data is created or changes is known as its velocity. The various forms and formats of data obtained from both structured and unstructured sources are examples of variety.In addition to the quantity of tables, records, files, or transactions, BD can also be quantified by size in TBs or PBs. Furthermore, the fact that BD now comes from more sources than ever before—including IoT data—is one of the things that really makes it big.
The state-of-the-art in BD is streaming data, which is gathered live from websites. The addition of a fourth V, veracity, has been suggested by certain scholars and organizations. The emphasis on truthfulness is the quality of the data. According to Elgendy and Elragal (2014), this classifies BD quality as good, bad, or undefined because of data ambiguity, approximations, latency, incompleteness, and inconsistency.

3.2 Data Science

DS is the methodical process of removing knowledge and useful patterns from data that are not immediately apparent (Dhar, 2013; Kelleher and Tierney, 2018). Its objectives are to promote organizational DM, advance research, and make a data-driven society possible (Ahalt, 2013). The definition demonstrates how DS is similar to business analytics, science, and scientific methods. DS, or "principles and procedures for the systematic pursuit of knowledge involving the recognition and formulation of a problem, the collection of data through observation and experiment, and Naturally, there are many parallels between the definition of science and the scientific method and "the formulation and testing of hypotheses" (Merriam-Webster, 2022)."Knowledge" in the context of decision support systems (DS) and related domains refers to conclusions and assertions that can be drawn from factual data analysis (Rizk and Elragal)

3.3 Artificial Intelligence and Machine Learning

AI is being used in our daily lives at an exponentially higher rate"A computer system with artificial intelligence (AI) is built to interact with the outside world using intelligent behaviors (like assessing

situations and recognizing speech) and capabilities (like visual perception and speech recognition). the available information and then choosing the most logical course of action to achieve a stated goal) that we would think of as essentially human," according to Luckin et al. (Luckin et al., 2016). AI is also defined as a branch of science that helps machines find solutions to difficult problems that are more human-like. This basically means that characteristics of human intelligence are transferred to algorithms. Even though AI and computer science are closely related, it also has connections to many other important fields.
The tagline for the now-defunct computer company Thinking Machines, Inc., which read, "making machines that will be proud of us," may have been the most fascinating definition (Murphy, 2000). The term artificial intelligence (AI) is contentious because it raises questions about whether a machine can ever be intelligent. Because of this, many researchers refer to their work as "intelligent systems" or "knowledge-based systems" in order to avoid the controversy surrounding the term artificial intelligence (Murphy, 2000). AI is permeating every aspect of our lives with new applications, from machine learning to robotics and other AI-enabled technologies.

3.4 Internet of Things

The phrase "Internet of Things" was first used in 1998 by Kevin Ashton. Any existing objects, whether they communicate or not, are considered things in the Internet of Things. The Internet of Things architecture is regarded as a three-layer technology. The perception layer, the network layer, and the application layer are these three layers. IoT is built on machine-to-machine (M2M) communications. The IoT allows two machines to communicate with each other without the need for human intervention (Aazam et al., 2014).
Hardware, software, and physical objects are all combined in the Internet of Things ecosystem to enable communication between them. It's a complex network of uniquely identifiable "things," all of which are linked to servers providing useful and efficient services. They can communicate with each other and the outside world by sending pertinent data from both the virtual and physical worlds. These things possess the capacity to respond autonomously to occurrences in the outside world. All of these processes have the ability to start specific actions and provide services through M2M communication or human intervention (Ahmadi et al., 2019; Hussain et al., 2022).
IoT is being used in a number of fields, including self-driving cars, smart energy, smart cities, smart homes, connected industry 4.0, smart agriculture, and smart healthcare. The healthcare industry will continue to rely more and more on IoT technology as it searches for new and creative ways to provide services while reducing costs and raising quality. By using these technologies, patients can apply the principles of self-care, which leads to improved self-management, more affordable healthcare services, and higher patient satisfaction.

4. Health Care System

The primary components of the current healthcare system will be discussed in this section. First, records pertaining to patients' demographics, practitioners, finances, health, and other areas. These serve as the cornerstones for creating patient profiles, creating treatment schedules, and other tasks. Then there is data, which is necessary for records and even for an established company to exist. Furthermore, the efficacy of the treatment and/or recovery plan is contingent upon the diagnosis and biomarkers, which are critical to the cure of any given patient. Precision medicine is an important and developing field that involves the use of genetic variations and gene libraries to help practitioners take a completely different approach when it comes to treatment plans or changing lifestyle habits for patients. Furthermore, when working with patients, it's important to remember that convenience greatly influences their adherence to prescriptions. In social forecasting, social media insights have the potential to identify and explain a variety of undesirable social behaviors and disease outbreaks. As such, they may aid in the prevention of future events or at the very least, help us get ready for them.
The truth about creating and keeping health records in the healthcare system will be discussed in the following subsection.

4.1 Electronic Health Records

Due to the current economic climate, medical facilities and healthcare providers are largely dependent on paid services, which is impeding the advancement of technology in these fields. Advances in technology have led to an abundance of medical data from multiple sectors. However, the unstructured, noisy, and inadequately annotated data gathered from diverse sources is not fully utilized to produce pertinent insights for therapeutic applications (Wang and Alexander, 2019).

Nonetheless, hospitals were encouraged to adopt electronic health records (EHR) by the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009. The hospital's EHR contains information on patient demographics, clinical notes, prescriptions, procedures, lab test results, diagnoses, and more. EHR data can help with forecasting hospital length of stay, predicting patients' chances of readmission, finding similarities among patients, integrating genetic data for personalized treatment, and selecting therapies. In spite of this, practitioners are reluctant to use these technologies due to the high heterogeneity, which increases the possibility of missing or incorrect entries. This is mainly because abductive reasoning is still needed to obtain clinical insights from these technologies in order to carry out an effective diagnosis.

Finding appropriate ways to use EHR for patient diagnosis is still necessary, despite hospitals using EHR for many corporate and administrative tasks, including asset and transfer management, patient logging, and primarily financial transactions. However, a number of challenging integration issues, labeled data scarcity for model training, and privacy concerns obstruct the effective use of these systems to generate quality care (Harerimana et al., 2019). You'll learn about some data collection instruments, like biosensors, in the next subsection.

4.2 Data collection and wearable biosensors

The cost of healthcare has increased in recent years, and the majority of patients must remain in hospitals while receiving treatment. With IoT technologies, these challenges can be addressed and patients can be remotely monitored. The World Health Organization (WHO) created a list of qualities—ASSURED, which stands for affordable, sensitive, specific, user-friendly, rapid treatment and robust use, equipment-free, and lastly, delivered to people in need—that constitute a suitable diagnosis test for resource-constrained sites (WHO, 2006). A broader multidisciplinary healthcare initiative to use mHealth to enhance data collection, diagnosis, treatment, and health insights has included wearables, also known as wearable biosensors.

In order to translate physiological characteristics from their raw form into meaningful digital health information, biomedical sensors gather and transform biomedical signal variables into electrical impulses. An electronic system and a biological system are connected by a biomedical sensor. According to scientific classification, biomedical sensors can be either physical or chemical (gas, electrochemical, photometric, or bioanalytic). While chemical sensors measure the concentrations of chemicals, physical sensors measure physical quantities such as body temperature, blood flow, blood pressure, muscle displacement, bone growth, and skin moisture (Aileni et al., 2015).

IoT technologies allow for the quick diagnosis and treatment of health issues before they become serious, reduce the cost of healthcare services, and gather and share real-time health data from patients to healthcare providers.

People's life expectancy has increased, and the WHO study on aging and disability indicates that older people are more susceptible to chronic illnesses, disabilities, and hospitalizations (Marengoni et al., 2011). Homecare services will soon replace hospital-to-home care in the delivery of healthcare. One of the most remarkable applications of Wireless Sensor Networks (WSN) is home monitoring, which uses heterogeneous sensors to identify human activity. It is becoming more and more common to integrate different Internet of Things components into medical and home care systems, especially for events like fall and seizure detection. As a result, during seizures, caregivers can give better care and act quickly to prevent potentially dangerous situations. A number of diagnostic and biomarker detection methods will be covered in the subsection below.

4.3 Diagnosis and biomarker detection

A person's physiological state changes in response to the course of their disease as it advances. A biomarker is any property that can be quantified and evaluated to indicate biological processes, pathogenic processes, pharmacologic reactions to therapeutic intervention, or any other measurable diagnostic indicator for determining the presence or risk of a disease. Examples of biomarkers include mRNA expression patterns, circulating DNA and tumor cells, proteins, proteomic patterns, lipids, metabolites, imaging modalities, or electrical signals. These signals, also known as biomarkers, can be found in tissues and/or bodily fluids. Accurate, usually non-invasive, and simple disease biomarker detection can improve disease screening, diagnosis, prognosis, and recovery—even in point-of-care (POC) settings. Consequently, early and timely discovery of disease biomarkers can limit the spread of infectious diseases and drastically lower the death rates from infectious diseases, cancer, and strokes.

4.4 Precision medicine

Based on patient similarities, personalized predictive analytics is a new method of delivering healthcare. When a patient needs treatment, similar cases are found in historical databases, observations are made based on prior documentation, and customized analyses are carried out based on the patient's genetic makeup. Drug recommendation systems use this technique to identify risk factors for similar patients and offer customized medical care. Individual characteristics like the environment, omics (genomics, metabolomics, proteomics, etc.), phenotypic, social, and psychological factors are the main focus of precision medicine. It is patient-centered, resource-intensive, and data-intensive. According to Wang and Alexander (2020), the process starts with the gathering of data from whole genome sequencing. BDA can then make interpretations and support precision medicine based on data similarities of prior patients. By enabling doctors to anticipate and prevent illnesses, customize treatments, and eventually improve patient outcomes, precision medicine has the potential to completely transform the way healthcare is provided.

4.5 Patient compliance

Diabetes Mellitus is another issue facing the healthcare industry. To effectively manage their condition, diabetics need to check their blood glucose levels on a regular basis. Testing blood drops released by a needle prick to the finger is commonly done using a blood glucose meter. The type of diabetes and the medications taken usually dictate how frequently tests are conducted; daily testing is essential, though. This type of testing can be difficult for diabetics; problems with self-monitoring, contamination, test strip cost, and needle phobia are all barriers to good blood glucose control. Luckily, status norms are about to change in the field of health informatics, meaning that finger-prick testing for blood glucose monitoring may soon become outdated! One health analytics application that aims to improve patient compliance is diabetes skin patches.

Last but not least, social media insights have the potential to produce information that, if untraced, could endanger a great deal of lives or even help us understand and stop actions or even prepare for disease outbreaks. Further information regarding social forecasting can be found in the final subsection.

5. Healthcare analytics

In the subsections that follow, we examine how various studies have used BDA, DS, AI, ML, or IoT technologies to address healthcare issues or offer solutions as a result of the interconnectedness between (modern) healthcare and DS.

5.1 Big data in healthcare analytics

BDA's advantages have led to an increase in its use across a range of industries, including medical research, healthcare services, and other fields (Dadkhah and Lagzian, 2019). By managing data-driven choices, BDA can enhance patient care by providing a more thorough understanding of medical issues and available treatments. Among the methods used in the healthcare industry are wearables, wearable AI, and the Internet of Things (Wang and Alexander, 2020). To make sense of BD, for example, industry-specific medicine leverages AI, next-generation technologies, and IoT. IoT-based smart healthcare architecture has progressed for all users during exercise; an artificial neural network (ANN) model is utilized by the Bayesian belief network to predict a patient's health-related vulnerability (Awrahman et al., 2022). Additionally, to classify, segment, cluster, and analyze health data, data warehouse technologies are used in the integration of healthcare data management systems (Andreu-Perez et al., 2015).

5.2 Data science in healthcare analytics

Disease analytics is one application of DS in healthcare. People can gain a better understanding of diseases by using disease analytics, healthcare analytics, and/or medical analytics to identify characteristics associated with certain diseases. It therefore assists in both the condition's prevention and treatment. Diseases that cause discomfort, dysfunction, distress, or even death in those who are infected and those who are close to them are generally referred to as diseases (Leung et al., 2021). Another example of the application of DS in healthcare is the creation of a social DA pipeline that enables analysts to use social data to look into suspected online radicalization. In order to represent and comprehend the factors that motivate extreme and illegal behavior, novel cognitive graph, entity, and connection concepts are introduced. The idea of a "knowledge lake" has been developed to provide the basis for BDA through the automated curation of unprocessed social media data and its subsequent processing to extract insights. By adding characteristics related to social actor behavior to social objects (like a tweet on Twitter), they intended to increase the size of the knowledge lake (Beheshti et al., 2021).

HCloud is one example of a cloud computing service used for medical applications, such as early illness warning systems and data analysis of physiological signals. Rather than making use of the full computational capacity of cloud platforms, cloud computing applications for the medical field are concerned with the storage, access, and management of private health information.

6.Conclusion

This study is an attempt to address the general request from researchers to look into "how" DS might assist the healthcare industry in addressing and resolving present issues (Dadkhah and Lagzian, 2019; Awrahman et al., 2022). The majority of the field's research has focused on "why" DS should be used to address healthcare issues. But not enough thought has been given to "how" they should be addressed. Thus, by offering a thorough examination of the applications of modern technologies like DS, BD, AI, ML, and IoT in the healthcare sector, this study adds to the corpus of knowledge.

A literature review, like the one conducted for this study, builds a solid framework for increasing our understanding of the subject matter. It facilitates the development of theories and identifies areas of research that merit more investigation. The purpose of a literature review study is to identify pertinent sources for a topic that a specific study is looking into. As a result, it makes a significant contribution to the rigor and relevance of research. Avoiding the reinvestigation of the known improves relevance. Reliance on the underlying body of knowledge is where rigor originates. There is no denying the importance of literature review studies (Webster and Watson, 2002).

Regarding the suggested research agenda, the study identifies research gaps and proposes research questions related to the technical difficulties in articulating the data architecture, the explainability and transparency of algorithms, the compelling privacy and security issues, and the legislative barriers that could be investigated and addressed by researchers, practitioners, and government healthcare agencies and officials. To the best of our knowledge, no literature has addressed the integration of DS in the healthcare industry or offered suggestions for future studies or approaches by practitioners. For example, the majority of studies have focused on the technical, societal, cultural, and legal obstacles that prevent the adoption of DS solutions in the healthcare sector. It hasn't been thoroughly examined how these adoption barriers need to be addressed in an effective manner. The literature review indicates that legislative barriers, or legal and regulatory obstacles that could prevent the adoption and use of data-driven solutions and DS technologies in the healthcare industry, are just one type of these barriers. Legislative barriers may pertain to the following: interoperability standards (Sarkar, 2017; Wang and Alexander, 2020); licensing and intellectual property (Ahmadi et al., 2019); ethics of healthcare and consent (Ahmadi et al., 2019); data privacy and security regulations (Aileni et al., 2015; Abouelmehdi et al., 2018; Harerimana et al., 2019; Meszaros et al., 2022). Effective cooperation between healthcare organizations, legal professionals, legislators, and technology suppliers is essential to removing legislative obstacles. To protect patient privacy and safety, it is crucial to approach these challenges thoughtfully and make sure that DS initiatives in healthcare comply with all applicable laws and regulations. Finally, we hope that by offering a thorough review, individuals who are interested in healthcare research will be able to learn about the current state of the field and contribute to its advancement.

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