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Recent Advances of Artificial Intelligence in Healthcare: A Systematic Literature Review

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Abstract: The implementation of artificial intelligence (AI) is driving significant transformation inside the administrative and clinical workflows of healthcare organizations at an accelerated rate. This modification highlights the significant impact that AI has on a variety of tasks, especially in health procedures relating to early detection and diagnosis. Papers done in the past imply that AI has the potential to increase the overall quality of services provided in the healthcare industry. There have been reports that technology based on AI can improve the quality of human existence by making life simpler, safer, and more productive. A comprehensive analysis of previous scholarly research on the use of AI in the health area is provided in this research in the form of a literature review. In order to propose a classification framework, the review took into consideration 132 academic publications sourced from scholarly sources. The presentation covers both the benefits and the issues that AI capabilities provide for individuals, medical professionals, corporations, and the health industry. In addition, the social and ethical implications of AI are examined in the context of the output of value-added medical services for decision-making processes in healthcare, privacy and security measures for patient data, and health monitoring capabilities.

Keywords: artificial intelligence; digital health; healthcare; healthcare systems; literature review

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1. Introduction

Since the beginning of the industrial revolution, there has been a significant increase in the importance placed on technology in terms of both output and growth [1–3]. This trend is expected to continue. According to Kaplan and Haenlein's research from 2020 [4], technological advances in machines have supplanted laborious and manual tasks, hence contributing to the progression of human growth. In a variety of industries, people can now replace manual labor with greater mental abilities and cognitive levels thanks to artificial intelligence (AI), a crucial technical advancement [5,6]. Beyond the assistance that machines provide for physical labor, AI is an important technological development that has allowed people to replace manual labor with more complex mental and intellectual levels [7,8]. AI is a field of study in science and technology that aims to make it possible for intelligent computers and computer programs to do tasks that have historically been deemed to require human intelligence. As a result, one of the most appealing aspects of AI is the fact that it can carry out a wide variety of tasks that humans are capable of, learn from previous experiences, and adjust to novel inputs and settings [4,9].

AI uses pertinent information sources in order to achieve improved performance for a range of different activities. Over the past few years, AI has made rapid advancements and has been deployed to provide many benefits across a variety of industries, including the essential healthcare industry [10–12]. One of the industries that has greatly benefited from AI is the healthcare industry. AI has presently electronically changed the medical system into an automated version in numerous domains. As a result, in some programs, humans are presently only needed to carry out essential duties in medical practice, such as handling patients and medical resources [13–15], rendering complex processes to be handled by or dependent on AI components. AI-based healthcare systems are fast evolving, especially for early detection and diagnostic applications [15–18]. As a result of these advancements, AI is now capable of doing activities that people are often unable to complete with the same speed, simplicity, reliability, and diligence that AI can provide at a lower cost [19,20]. According to Tobore et al. [21], technical progress made possible by the digitization of healthcare can help overcome extra problems if developers of information systems (IS) are able to successfully create AI systems to carry out certain jobs [22]. For instance, AI has the potential to greatly improve patient care as well as reducing costs associated with healthcare [17,23,24]. The ever-increasing human population is projected to raise the demand for medical services to be given at a rapid pace; hence, innovative AI solutions are required in the medical sector in order to increase both efficacy and effectiveness without a corresponding rise in expenses [25,26]. In this particular domain, AI continues to play a pioneering role in providing novel solutions [13,27].

Recent rapid technological breakthroughs, in particular in the field of AI, have already aided the management of the growth of the medical sector. Recent AI technologies include big data, algorithms for learning applications, and robots. These technologies are used in the healthcare business to track, identify, and assess hazards as well as advantages [28–30]. The healthcare industry places a significant emphasis on medical data and analytics as a means to strengthen processes and make the administration of medical services more straightforward. In recent years, the amount of medical data that has been obtained as well as their dimensions have increased at an exponential rate. For instance, healthcare providers, scientists, and healthcare consumers create enormous quantities of data from multiple monitoring devices which people are growing to utilize in ordinary situations aside from the need for medical attention [31–33]. These data can be used to increase the quality of care that patients receive [13,34]. This function is often carried out with the assistance of machine learning algorithms, which are backed by data storage and processing power [35,36]. For instance, by keeping a close eye on a patient's behavior patterns and recording them every day, medical professionals may be able to make trustworthy predictions. As a consequence of this, AI may offer recommendations regarding diagnosis, healthcare treatment, therapeutic perspectives, and strategies for alleviating wellness decline and supporting proactive measures that hinder patient conditions from deteriorating, thereby improving patient results throughout different stages of diagnosis and illness, as well as medication prescription and use. Hospitals that are on the cutting edge of technology are currently investigating the use of AI technologies to enhance clinical accuracy [20] and reduce the cost of operating procedures [19,20]. AI enables medical personnel and patients to make informed decisions regarding treatment plans by offering thorough information on a number of treatment options [37,38].

Additional study is required on both the practical and theoretical components of AI in order to achieve a comprehensive understanding of these facets of AI [39,40]. In order to accomplish this goal, the aim of this paper is to describe the most recent developments in the implementation of AI in the medical sector. By applying the methodology developed by Webster and Watson [41] to the investigation of previous research, this piece makes a significant theoretical contribution in that it offers an authoritative theoretical foundation for the recently published research. This methodology is concept-driven, and it enables the study of a variety of concepts described in this article as well as a more readily understandable comprehension of continuing developments. Academics will have the opportunity to expand their grasp of what past researchers have done in the medical sector and the constraints of momentum research, both of which will be of benefit to them. This paper may be of some significance to scholars who are currently researching the implementation of AI in the medical field, as well as to academics who have been introduced to the field but have been focusing on inspecting more explicit experiences into where the most recent research subjects are concerned in this literature and how they may contribute to them.

2. Literature Review Methodology

According to Kamboj and Rahman [42], systematic reviews are becoming increasingly relevant in all fields of study, and they are also becoming increasingly accepted in the combination fields of the technology and healthcare industries. Systematic reviews are followed by industry professionals and scholars working in the information technology and medical sectors in order to keep current in their respective fields. These reviews are also frequently utilized as a jumping-off point for the development of new technology guidelines developed by Moher et al. [43] for use in a variety of other fields, involving health. When it comes to making judgments, IT professionals and medical experts do not rely on the findings of a single study. According to Abbas et al. [44], some studies are flawed because they are based on inadequate data or because they arouse preconceived notions, both of which lead to inconclusive findings. IT professionals and healthcare professionals are required to rely on robust evidence to inform practice in their professional and academic work, respectively.

A literature review approach that consists of three stages was put forward by Webster and Watson [41], and it has been recently used in IS research into management [45,46]. Articles have been found that embrace this methodology, and they use it to conduct their literature reviews. At first, a search was conducted through the most recent literature reviews in order to select the databases and keywords for the primary search. After that, the forward search was implemented to examine the citations of the selected articles, and, finally, the backward search was carried out in order to explore the references of the selected articles so that their total could be increased. Following the selection of the articles, they were arranged according to the content they contained.

Previous literature reviews from 2022 to 2023 are presented in order to bring the present literature review up to date with the most recent information pertaining to the subject of AI in healthcare, to analyze the history of information pertaining to this subject, and to investigate distinct research questions whose answers are dependent on the findings of earlier investigations. In addition, previous literature reviews provide a concise description of the literature review approaches used by scholars, highlighting both the usefulness of these methodologies and the inadequacies in their implementation. An overview of the most recent literature reviews pertaining to this area of research is provided in Table 1.

Table 1. Previous literature reviews.

Authors	Year	Methodology
Mahdi et al. [47]	2023	In areas where AI is now playing a substantial role in clinical dentistry, this study attempts to systematically review that role.
Vishwakarma et al. [48]	2023	The purpose of this study is to comprehend how AI helps create a robust and sustainable healthcare system.
Ali et al. [2]	2023	This paper gives a thorough analysis of scholarly works on the use of AI in the healthcare industry. A total of 180 articles have been examined to present a classification framework based on four dimensions: AI-enabled healthcare benefits, challenges, methodologies, and functionalities.
Siala and Wang [49]	2022	This paper suggests a responsible AI initiative framework that includes five key themes for AI solution developers, healthcare professionals, and policy makers by combining pertinent knowledge from AI governance and ethics. These themes include inclusivity, fairness, inclusivity, sustainability, and transparency. A total of 253 papers were extracted from two databases.

The search was conducted in the databases Scopus, Web of Science, and PubMed using combinations of the following keywords: “artificial intelligence”, “AI”, and “health”. The papers we were looking for were published in peer-reviewed journals and conference proceedings. These were selected without giving priority to any particular time period in history. There were no exceptions made for books, book chapters, technical reports, or working papers. The papers were filed under "Computer Science" and "Business Management and Accounting," respectively.

The utilization of keywords throughout the various databases resulted in the collection of a total of 3070 documents. The restrictions imposed by language and the many sources of publication led to a decline in the number of papers in 1041. After examining the publications' titles, we determined that 497 of them were pertinent to the purpose of this paper. After that, we looked through their abstracts, and 389 of them were accepted. We analyzed the titles and abstracts to see whether or not they effectively made use of the search terms. Following this, the content of the remaining papers was screened, and only those papers that were deemed "fit for purpose" in terms of adding to the overall response to the research questions were considered relevant and hence included. Several papers were omitted from the review since the entire text of those papers was unavailable. These pieces were published in the proceedings of the conference, but the complete texts of the articles were not available. They were subjected to a cursory investigation so that it might be confirmed. This subsequent review demonstrated that each and every one of them ought to be included. The co-authors talked about the extent to which each paper added more value to the overall goal of the paper. As a direct result of this, the complete contents of 221 papers were examined. There were 116 papers that needed to be included, and the duplicate articles have been eliminated. These articles now have an additional six in the "backward search" category. In addition, ten additional papers were obtained through a "forward search," bringing the total number of papers that were investigated to 132 (Figure 1). All the authors who contributed to the paper reviewed and accepted the final list.

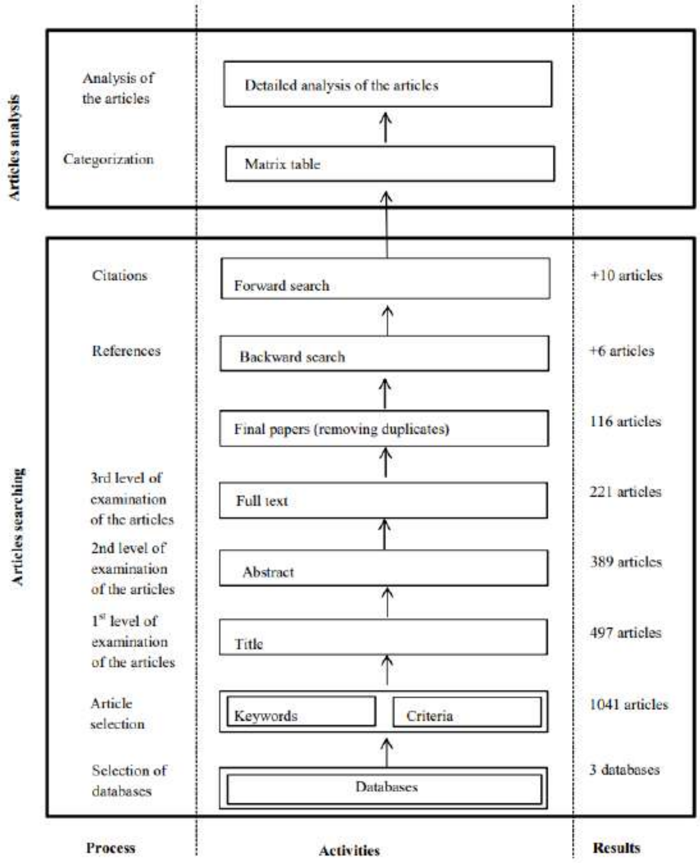

Figure 1. Article selection process.

A categorization framework was used to conduct an analysis of 132 different papers. These articles have been assessed on four broad dimensions (healthcare activities using AI, advantages and disadvantages for the healthcare sector, ethical issues about AI, and social sustainability and AI) that will enable a better understanding of AI in healthcare research and, additionally, help future academics expand their knowledge in this field. With the help of the VosViewer software, Figures 2–4 illustrate the clusters that emerged from the heat map after focusing on the primary ideas.

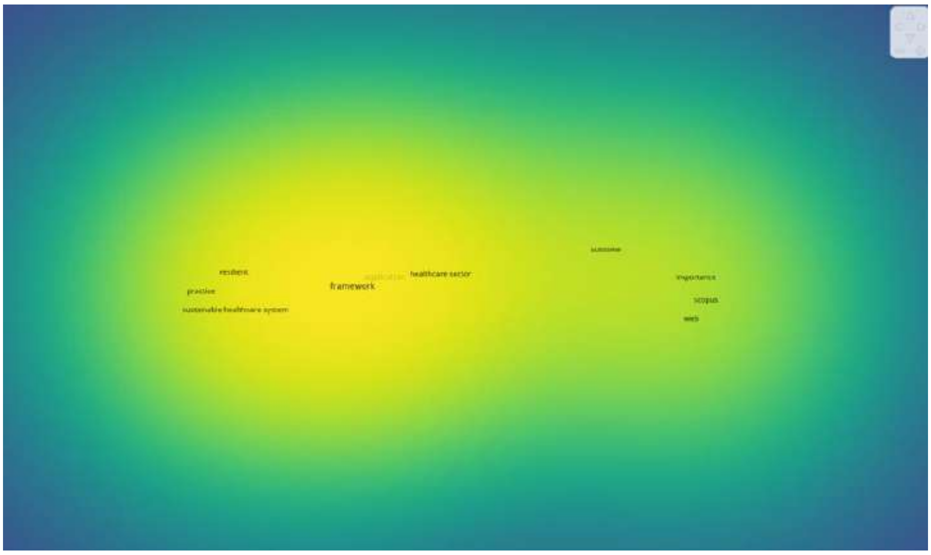

Figure 2. Heat map for cluster 1.

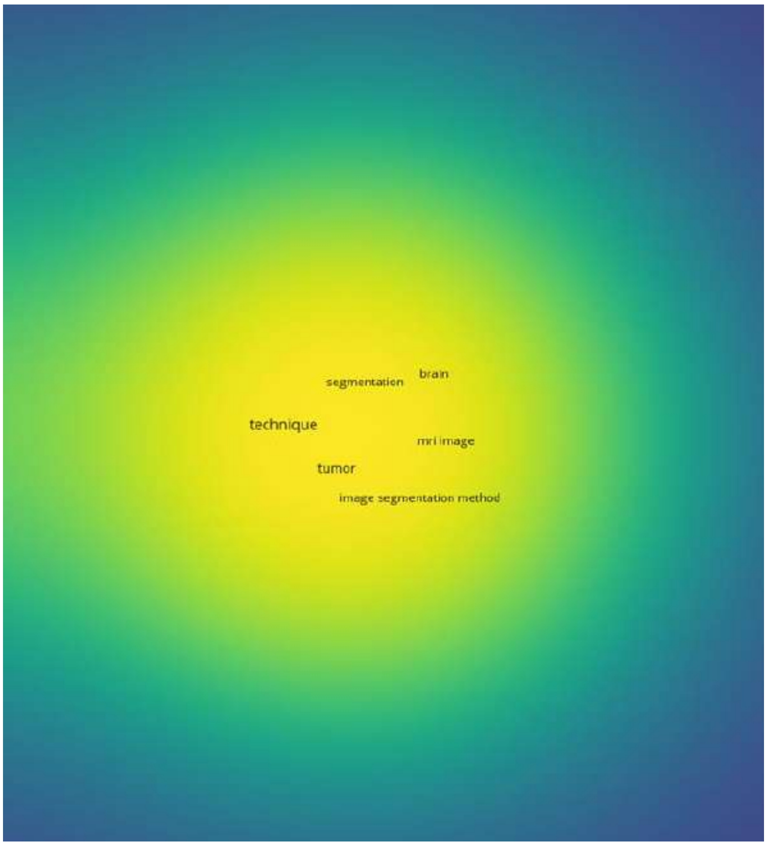

Figure 3. Heat map for cluster 2.

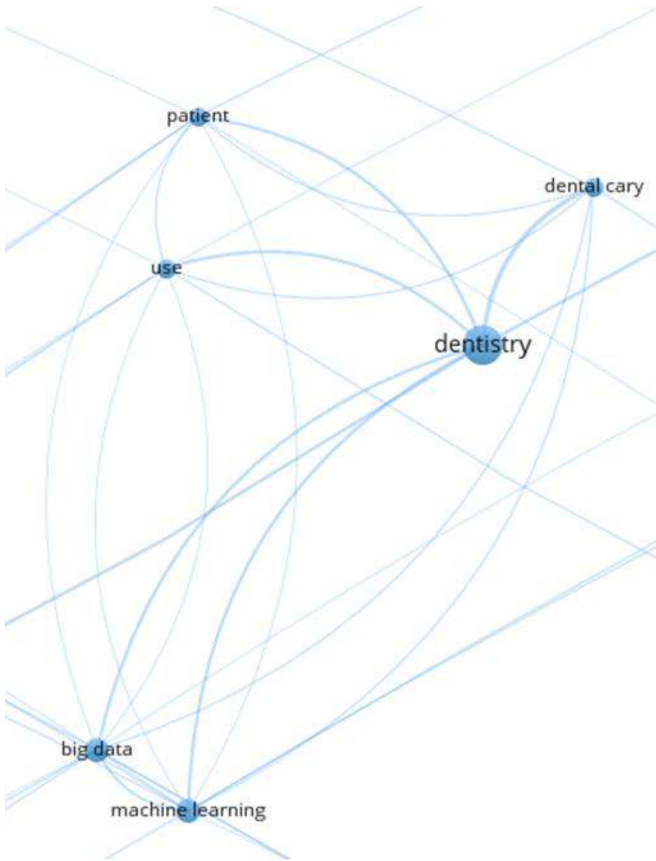

Figure 4. Heat map for cluster 3.

3. Classification Framework for Analysis

3.1. Healthcare Activities Using AI

For those aspects of healthcare that make use of AI in the healthcare industry, AI technology can serve a variety of purposes, including for clinics, patients, and the industry as a whole. The use of technology in clinics enables them to make decisions [10,50,51], collect up-to-date information [20,52], and share information [53–56].

Furthermore, machine learning helps enhance decision making by offering an apparatus for medical practitioners and academics to extract concealed information from the enormous quantity of data that is available. This knowledge is inaccessible if human effort alone is relied upon to make the discovery. This is another way that machine learning helps improve decision making. The use of machine learning to enhance and automate the decision-making process in the healthcare industry has been the subject of extensive research [10–13,19,57–63].

Patients are the primary focus of activities related to healthcare. There are many other applications that can make use of AI technologies, such as scheduling appointments and monitoring patients. AI and other technologies primarily have applications in the areas of patient diagnosis [14,50,51,64,65], treatment [10,66–68], consultation [15,19,51], and health monitoring [27,69,70].

Numerous individuals are in relatively good condition but nevertheless require round-the-clock observation. Patients of this age range may be healthy or in a condition where they are unable to take care of themselves, and they may also be seniors who require continuous attention for reasons relating to their health or their advanced years. When following typical patient monitoring tactics, this kind of health monitoring takes up a lot of time, human resources, and financial resources, which can be hard, but these things simply cannot be avoided for the sake of the patient's safety and wellbeing. The use of remote patient monitoring is a new approach to the problem. The management of health and illness with the aim of treating or diagnosing illness using IT is the subject of remote patient monitoring, a developing area of healthcare [71]. The use of remote patient monitoring offers a number of benefits, not only to patients but also to hospitals. In addition, telehealth networks are becoming increasingly significant, particularly in light of the COVID-19 epidemic.

By limiting the frequency of false warnings and relieving practitioners' burdens, AI minimizes hospital loads, resource consumption, hospital occupancy, and lost time and effort in unneeded medical intervention. This is accomplished by freeing up practitioners' time to focus on more important activities. In addition, there are a lot of benefits that patients, particularly older patients, can get from having remote patient monitoring. In the first place, it prevents them from squandering their time, energy, and resources by reducing the number of unneeded trips to the hospital. Second, it plays a significant role in the protection and wellbeing of the patient by providing potentially life-saving signals when the patient's condition requires immediate medical attention. When the patient is in poor health and is unable to call for aid, this method becomes much more effective. A significant amount of work has been put into the development and testing of health monitoring systems that integrate several types of biomedical information recovery devices and machine learning [27,72–74]. For instance, Khan et al. [72] advocate for the implementation of AI in medical practices as a solution to the ever-increasing volume of patients. According to them, incorporating AI into clinical settings enables medical professionals to more effectively manage the continuous flow of biomedical information. The authors present a prototype that is capable of gathering real-time biological data in order to evaluate the general condition of an individual's heart at any time and in any location. The data that were collected were processed by the prototype with the help of an algorithm that made use of a number of different machine-learning approaches. The results of these approaches are created through the use of ensemble methods. According to the authors, the model was successful in getting rid of pointless and repetitive duties, which freed up more time for more productive treatment tasks and decreased the amount of wasted money and effort.

Both AI and the internet of things have been the subject of a significant amount of research that has been conducted in an effort to better advance the medical industry. This latter technology is helpful in integrating the infrastructure of the internet and sensor networks, both of which provide a useful stream of data that can be examined using AI models [27,73–79].

The diagnosis is a very important first step on the road to successful therapy. Despite this, it can be quite difficult for many diseases, particularly in the earlier phases of their development. Despite this, early detection has the potential to be a game-changer for various diseases since it can save patients, doctors, and even hospitals huge amounts of time and resources. The potential of AI in early diagnosis has been the subject of a significant amount of study [35,73,80–83]. Early detection of certain diseases, such as cancer, can dramatically impact the course of treatment and recovery. Early detection of cancer can significantly improve a patient's odds of surviving the disease and responding favorably to therapy by elevating the percentage of treatable cases. When it comes to the early detection of cancer before it has had time to spread, this can be much more helpful.

Gayathri et al. [80] proposed a model that uses fuzzy logic to determine whether or not a woman is at risk for developing breast cancer. By employing linear discriminant analysis (LDA) as a method for feature reduction, this model makes an effort to shorten the amount of time required for diagnosis. Katarya and Srinivas [81] conducted a study comparing several AI algorithms by making use of the Cleveland database that was already in existence. They investigated a variety of models and found that decision trees and naive Bayes performed the best. In order to attain a high level of accuracy, the authors suggest making use of search methods for feature selection. Murray et al. [84] investigate potential solutions based on machine learning to address the semantic issues that are now being faced by healthcare practitioners.

3.2. Advantages and Drawbacks for the Healthcare Sector

Contrasting positive and negative aspects of the healthcare industry, AI provides a number of advantages to people, some of which include streamlined decision making [10–12,19,61], health surveillance, including monitoring of elderly patients [13,53,69,72,85], early diagnosis [11,50,51,70,86,87] and process simplification [19,37,62].

The acquired medical data of individuals, which are frequently inconsistent, convoluted, and not standardized, are the primary source of the barriers that accrue to those persons. In addition to that, they frequently come in a high volume and have a variety of forms to choose from. AI may be considered extremely successful in assessing such kinds of big data while producing creative suggestions that are highly pertinent and important for medical practitioners, which will ultimately benefit patients in their care, diagnosis, and therapeutic options. Despite the fact that this presents an enormous obstacle for health practitioners, AI can be very operational in analyzing these types of big data. Decisions pertaining to diagnosis and therapy typically require a lot of both time and effort. AI is a practical answer to this problem since it has the potential to generate autonomous inferences with little or no involvement from a human being. This makes it an ideal tool for overcoming this obstacle. According to Kaur et al. [24], some studies claim that AI can even surpass humans in certain medical settings, such as those involving radiology, cardiology, and tumor identification.

Sqalli and Al-Thani [19] discuss the case of chronic diseases. They state that chronic diseases in particular are taxing on the medical industry regarding effort and cost. This is due to the fact that patients with chronic diseases need constant treatment, which requires them to contact their healthcare providers on a regular basis. There are some of these visits that are completely pointless, which results in a waste of time and resources. According to the authors, they conclude with a strategy that combines health coaching with AI in order to assist patients in more efficiently managing their chronic diseases and reduce the number of visits that are not essential. This system, which is very similar to the one proposed by Murray et al. [84], is made up of sensors that are able to collect biometric data, AI models that are able to create insights about health issues, and visual analytics tools that are able to display relevant data in graphical and textual formats.

AI applications and IT tools are used by organizations in order to cut costs [19,20,24,88], detect fraud [17,89], improve performance [10,27,51], and provide workflow assistance [14,37,53,90]. For example, Murray et al. [84] highlight the challenge of automatically extracting knowledge using medical IS. This difficulty is mostly due to the limited level of data standardization and integration that is present in these systems. In order to conquer these obstacles, the authors propose a synthetic network powered by AI. This is done on top of the original notes made by doctors in order to assure data normalization and integration from many sources. The operation of this network is comprised of three primary steps. First, it applies the transformation rules that have been stated to normalize the data. The data are then integrated after being transformed using ontologies that have been verified. In the end, it utilizes a model for data analytics in order to get useful information from the combined data. AI has been proposed as a solution for similar complications in the healthcare sector to reduce the consumption of resources [19,20,24,88].

Many studies have implemented AI as a solution for analogous challenges. The detection of fraudulent claims is another area in which AI can be of use to the healthcare industry. The insurance industry has a significant obstacle in the form of fraudulent activity involving health insurance. With the constant growth in data volume, an accompanying increase comes in the difficulty of detecting fraudulent activity. Detecting fraudulent claims in the health insurance industry has been an area of focus for a number of researchers [17,89,91–95]. In their article from 2015, Rawte and Anuradha [89] propose a hybrid system that detects duplicate insurance claims by combining the methods of clustering and classification. The authors point out that classification algorithms and clustering approaches on their own are not enough to identify duplicate claims. The authors suggest a model that consists of two stages as a solution to this problem. The first thing that has to be done is some claim clustering, which should be done using the evolving clustering approach. The output of the first step is used as input for the second phase, which is based on the SVM algorithm and uses the classification step.

Dhieb et al. [17] provide a structure for a health insurance system that makes use of extreme gradient acceleration (XGBoost). The goal of this framework is to reduce the amount of human interaction required, secure insurance activities, alert and notify consumers who pose a danger, identify erroneous information, and cut down on revenue losses for the insurance industry. When the XGboost algorithm was used to analyze data from a car insurance dataset, the findings showed that it attained considerable performance increases in comparison to other learning algorithms that are currently in use. These are just a few examples of how recent breakthroughs in AI have brought benefits to firms that have used AI systems [96–99].

There are a great number of benefits that can be brought to the realm of healthcare by expanding the use of AI technologies to this important sector. It helps lower the amount of time and money spent on therapy as well as the amount of resources that are used [100]. In addition, it shortens the amount of time needed to make a diagnosis and, as a result, the process of making a decision. This has a significant effect on treatment strategies and outcomes, and it may even be lifesaving in extreme circumstances. When carried out by a variety of healthcare professionals at a variety of health facilities, data exchange in the healthcare industry is an important component of individual wellbeing. In addition to this, it is essential for the development of scientific research. The article by Paranjape et al. [97] promotes the utilization of AI for educational purposes and presents a model which integrates AI into the training program for medical professionals. AI has the potential to be beneficial across the board in the healthcare industry.

The processing of certain AI algorithms requires a significant amount of data. Due to the ethical implications of such data, it can be challenging to gather data at times, particularly data pertaining to patients. If some classification and clustering methods are applied to a very small amount of data, the results may be quite accurate; nevertheless, this may not be practical or useful [60,64,84]. For AI methods to work well, the data must first be preprocessed. In particular, natural language processing must be performed extensively on text data before they can be used. One of the most difficult issues in medical data processing is the need to integrate several forms of data using the same algorithm at times [60,64,84]. This is one of the reasons why there are so many different types of algorithms. Data can be gathered for medical purposes from a wide variety of sources and forms, including medical imaging, 3D video sequences, still photographs, and quantitative data. The analysis of healthcare data presents many challenges, one of which is the collection of accurate, trustworthy, and effective data.

The majority of AI's applications in healthcare are focused on improving the diagnostic process. Incorrect conclusions reached through computerized diagnosis could have extremely negative consequences. Sometimes the data collected from hospitals are not of high enough quality, and other times they are just erroneous. According to Ling et al. [101], Hasan et al. [102], and Goldberg et al. [103], one of the most significant difficulties associated with processing medical data using AI is the presence of data mistakes. Another difficulty lies in the fact that decisions can sometimes be made incorrectly by machine learning algorithms. Several studies [104–107] have revealed possible decision-making challenges in the health area as well as their remedies. The field of healthcare is currently making extensive use of AI, IoT, and devices. However, not all of them are automated. Doctors make the ultimate choice, and the interaction between medical practitioners and the AI frameworks may result in inaccurate diagnoses and treatment outcomes [19,108–110].

3.3. Ethical Issues about AI

In the past few years, there has been an increasing amount of discussion on the ethics of AI in healthcare research [111,112]. A number of different ethical concepts have been recognized as potentially appropriate candidates for the design and development of AI systems. However, a significant portion of today's AI-driven research does not take into account the necessary ethical, regulatory, and practical factors for widespread use [113,114]. This is because there is not yet a single framework in place to control AI [115,116]. Despite the fact that AI ethical frameworks have undergone numerous modifications to reflect the complexity of AI ethical issues, they still do not offer much guidance as to what policies should be put in place to support ethical use of AI. This is true even if models for AI ethics have undergone numerous revisions to account for the complexity of these problems [115,117].

Accessing, altering, distributing, and using patient data all raise legitimate concerns with regard to the patient's right to privacy. Computing in the cloud and AI are two technologies that are increasingly being put to use in many applications within the medical sector. These systems are responsible for data collection, processing, storage, monitoring, and collaboration [86,96,118,119]. Despite the fact that these systems offer a number of benefits, there are also a number of obstacles associated with them, including ethical concerns, security concerns, consequences for users' privacy, and cybersecurity concerns. In most cases, healthcare facilities and government entities offer ethical protocols for the collection and dissemination of data. Even for the purposes of study, it is necessary to obtain permission from a government-approved authority in order to gather and utilize data [67,120]. Inequality, unemployment, humanity, dedication to cause, regulatory approaches, behavioral biases, demographic biases, and connecting biases are some of the other ethical concerns that have been raised in relation to AI in the context of healthcare and other industries [121,122]. Studies on limiting negative side effects, reward hacking, safe exploration, and robustness are being conducted as part of efforts to reduce the number of ethical concerns raised by applications of AI in the medical field [118,121,123,124]. Concerns have been raised by government officials concerning the impact that these automated processes will have on patients' rights. These worries have resulted in the creation of a number of regulations regarding the collection, processing, and utilization of technology, as well as the quality of such data and the gathering and analysis methods [96,124,125].

According to Chun [126] and Song and Kim [127], a perspective on virtue ethics can make a contribution to the development of responsible AI. The virtue ethics theory places more emphasis on the moral character or virtue of the person carrying out an activity in a certain context (what would a virtuous person do in a particular setting?), as opposed to the appropriateness of an action or the consequences of that conduct [128,129]. Different virtue ethicists have offered their own interpretations of the characteristics that make up a virtuous individual [129,130] (Audi, 2012; Unberath et al., 2020). Virtue ethics can help managers make better ethical decisions when it comes to management practices. Additionally, a company can use virtue ethics to "increase a firm's reputation and moral standing in the society in which it operates," to "direct a firm in its day-to-day activities and operations," and to "reduce the risks associated with using a service" [131,132]. This idea can be extrapolated to include healthcare providers who are implementing AI. Therefore, the concept of virtue ethics is a suitable theoretical basis to establish an accountable AI initiative framework in healthcare. This is due to the fact that previous research indicates that the existence of noble character characteristics (such as fairness and honesty) in an agent (person or organization) can positively impact the actions of that agent [126,129].

Healthcare professionals are still not fully aware of the potential ethical problems that emerging AI technologies could create when providing actual care [133,134]. The type of AI ethics training that should be included in order to prepare and instruct future medical professionals in the usage of AI technology appears to be unclear at the moment [135,136]. Privacy and surveillance, bias and discrimination, and possibly the most profound and challenging philosophical challenge of the day, the function of human judgment, are the three main ethical issues that AI raises for society. We are all aware of discussions regarding privacy protections and ways to eliminate bias in algorithmic decision making for sentencing, parole, and employment practices. In order to decide what regulations should be put in place, as well as the role that big tech and social media should play in our lives, organizations must carefully consider the ethical implications of what they do. We, as democratic citizens, must also educate ourselves about technology and its social and ethical implications.

3.4. Social Sustainability and AI

In recent years, there has been growing interest in AI applied to sustainability from both academics and practitioners. When using AI, one should give careful consideration to how it will affect society as a whole, particularly in terms of people's and the planet's health. Responsible use of AI in healthcare institutions is required in a way that strikes a balance between the needs of stakeholders, reduces ethical problems as much as possible, and generates revenues that will last. If a healthcare institution develops AI algorithms, either intentionally or unintentionally, that threaten human rights and wellbeing, then the business's reputation and credibility could be severely damaged. For instance, the unethical use of AI, such as substituting established health services with smart technology, has been called out as a problem that needs to be addressed [137]. According to Abramoff et al. [138], this has the potential to make existing health disparities even worse. The economic and social sustainability of healthcare organizations should be prioritized, and AI should be used to build solutions that support this goal. More specifically, they need to establish ethical governance policies that take socially undesirable behavior into account, address ethical issues during the early stages of the design of AI systems as well as after they have been put into operation, and incorporate AI ethics into their social responsibility strategy [139].

3.5. AI in Hospital Management

Recently, AI-supported technologies have been widely used in healthcare institutions to increase the effectiveness of medical resources and the quality of care provided. The knowledge-intensive healthcare sector has many prospects for innovation thanks to AI-based technologies, which include machine learning, natural language processing, and intelligent robotics [140,141]. Regarding its potential for revolutionary advancements in the treatment of human diseases and public health, AI has caught the interest of researchers, clinicians, technology and program developers, and consumers in a variety of disciplines [142].

Any healthcare organization's main goal is to offer their clients services that are personalized, predictive, preventative, and participatory. AI can significantly advance this area; hence, e-health can be defined as the fusion of AI with healthcare [143]. From a number of angles, including patient monitoring, medical diagnosis, prescribed therapy, and follow-up, e-health has altered the traditional culture of the healthcare sector. Healthcare personnel are held to a high standard, and investigations must be conducted correctly. Although accurate data extraction from the vast amount of available data is laborious, technology plays a significant role in overcoming all barriers. In terms of patient data management, advanced and speedy diagnosis, disease investigation, proposed therapy, and improved results, AI-enabled e-health systems outperform conventional systems. Therefore, a decrease in medical error boosts the efficiency of the healthcare system as a whole [144].

There is no doubt that the healthcare sectors have changed as a result of the use of AI technology. Due to improved patient results, it has altered the revolution in treatment methods. Complex procedures can be automated effectively by speeding up decision making and improving accuracy. Quick data extraction, time-requirement optimization, quick solutions, avoidance of redundancy, and, most significantly, enhanced speed while handling large amounts of data are all facilitated by AI. AI assists electronic health records with voice-based requests and performs patient complications, analysis, and measures documents in specified formats. Such a method makes the overall procedure for extracting explicit patient information relatively convenient. Additionally, it has the ability to transform narration into a task that may be completed immediately [144].

3.6. AI and Machine Learning in Disease Diagnosis

AI techniques, from machine learning to deep learning, play a critical role in many areas related to health, such as the development of new healthcare systems, the management of patient data, and the treatment of illnesses [145]. The diagnosis of various diseases can also be made most effectively using AI approaches. There are unprecedented opportunities to recover patient and clinical group results and lower expenses thanks to the use of computerized reasoning (AI) in healthcare [145].

Health is the most important part of life, and "early diagnosis saves lives" is a well-known truth. A precise ailment can be identified by a doctor by using disease diagnosis as a process of determining something based on pre-existing classification [144]. In general, the procedure is wellorganized and patient-focused. A person attends a clinic or hospital when they experience certain health issues as indicated by certain signs. The doctor first gathers the patient's medical history during the visit and, if necessary, does a physical examination. A disease diagnosis is made and an appropriate course of treatment is recommended based on the collection, fusion, and interpretation of all available information. Patients must visit the hospital for observation and corrective action during therapy, although the intended outcomes have been reached. If necessary, all of this specific information will be used for another patient [144].

Today, AI has changed practically every area of our daily lives. Researchers have tried to use AI for early disease diagnosis and have had some success because health is very important and medical-related data are always growing. Programs with AI capabilities have been created and trained using data sets, which are collections of past patient diagnoses and treatments, present patient history, symptoms, lab findings, and scan results When these algorithms or programs are running, they aid in decision making and even unobserved data aids in the prediction of exact disease-related information. Breast cancer, liver cancer, cervical cancer, kidney-related problems, hepatitis, dermatological, cataract, heart-related, pancreatic disorders, etc., are just a few of the conditions that require diagnosis [144,146].

Ideas from a variety of disciplines, including computational learning theory, artificial neural networks, statistics, stochastic modeling, genetic algorithms, and pattern recognition, are incorporated into machine learning. As a result, it comprises a broad category of techniques, as suggested by the type of manipulation that takes place during learning, such as closest neighbor or example-based learning, discriminant analysis, and Bayesian classifiers. Learning from patient data presents two or three challenges because these datasets are incomplete (missing parameter values), inaccurate (systematic or unexpected movements in the data), scarce (a variety of nonrepresentative patient records are not open), and inaccurate (inadequate parameter selection) [147].

The ability of machine learning to diagnose diseases, organize and categorize health information, and accelerate decision making in the health center will provide general practitioners more power. Huge amounts of information on each patient are recorded by the healthcare system, and humans find it laborious and challenging to sort through this information. Managers can create decision support models and interpretations of the data with the aid of machine learning techniques. They provide medical personnel with a fundamental method of data analysis and a more precise method of disease diagnosis [147].

Some people could suppose that doctors would soon become obsolete in light of scenarios where AI supports or enhances processes for diagnosis, treatment, and/or operation. To investigate the prospects and problems related to AI applications in the healthcare sector, it is crucial to first evaluate the role that AI can play. Based on numerous examples of real-world AI applications, it is clear that AI has a huge and diverse range of possible applications, ranging from the simplest operational process improvement to the most complex emergency patient therapies [140].

3.7. AI and Machine Learning in Remote Patient Monitoring

The world is currently expanding quickly as new technologies transform many industrial sectors. One of the many scientific tools that has a big impact on the healthcare sector is AI. One of the divisions of e-health, which has expanded dramatically, is remote patient monitoring [148]. AI-powered remote patient monitoring is a highly effective technique for managing common-to-chronic diseases. In order for remote patient monitoring to function, data must be gathered and sent to healthcare professionals via a linked device. As a result, the majority of healthcare institutions have implemented remote patient monitoring, shifting the traditional method of treatment in that direction. Patients have demonstrated trust, and even for high-risk patients, issues, diagnoses, health improvements, and other patient data may be easily tracked [144].

Depending on the type of device used to get the necessary patient data, the remote patient monitoring procedure may vary. The majority of wireless sensors are used to gather data, which are then transferred to the cloud and other servers for remote patient monitoring. AI algorithms are used in the analysis to provide clinical decision making, which is subsequently communicated to healthcare practitioners. In difficult diagnoses, the patient and doctor may interact personally, communicate by notification, or receive expert input. In recent times, there have been various programs that offer a good user interface for viewing available prescriptions, tracking patient health information, displaying treatment/doctor/hospital suggestions, and sending notifications [144].

There is no shadow of hesitation that in the years to come, the use of AI in the diagnosis and treatment of diseases will be accepted and acknowledged on a widespread scale. The use of a variety of AI methodologies, both structured and unstructured, for the various forms of data is one of the primary reasons for its exceptional capacity for extensive adaptation. Because of this property, the scope for identifying the disease is significantly expanded. When a disease is quickly diagnosed, therapy can begin much sooner and at a lower cost. The quantity of data associated with healthcare is expanding at an astounding rate. The AI-based system aids in understanding the features of a vast volume of medical data that are essential for clinical procedures to be assisted by. In addition to this, these algorithms are equipped with the ability to self-correct, which enhances both their accuracy and efficiency on the basis of feedback. The system that is based on AI approaches can also help clinicians by producing the most up-to-date medical knowledge from various resources such as journals, textbooks, clinical practices, and so on, which will ultimately lead to more effective patient care. The tools of artificial intelligence are able to forecast human genomes and prescribe treatments that are suitable, allowing patients completely individualized care. During the process of developing various functions, they are linked with human intellect in the form of problem-solving capacities, learning, and reasoning, which ultimately results in an increase in the effectiveness and capabilities of medical experts. Rule-based structures, case-based deduction, ambiguous models, computational neural networks, cellular automated processes, algorithms based on genetics, swarm cognitive ability, multi-agent systems, hybrid systems, reinforcement learning, and so on are some examples of the various methodologies that can be utilized [149].

Nucleic acid testing is associated with high levels of specificity and sensitivity and plays an important role in the field of molecular diagnosis, particularly with regards to the diagnosis of infectious diseases, neoplastic diseases, cancer biomarkers, genetic mutations, and genotyping, while also facilitating food safety control and environmental monitoring. In the field of molecular diagnosis, particularly in relation to the diagnosis of infectious diseases, neoplastic diseases, cancer biomarkers, genetic mutations, and genotyping, as well as facilitating food safety control and environmental monitoring, nucleic acid testing is associated with high levels of specificity and sensitivity. Nucleic acid testing has a number of important advantages over other techniques, such as immune detection and microbial culture, including high levels of sensitivity and accuracy and a short operational time window. As a result, nucleic acid testing can quickly diagnose specific conditions and subsequently enable early therapeutic intervention. The COVID-19 outbreak that began in early 2020 is still spreading on a worldwide scale. This virus continues to have catastrophic effects and a wide potential for spread. The COVID-19 epidemic was diagnosed and controlled with the help of nucleic acid testing. The spread of this epidemic is putting every nation's medical diagnostic capacity to the test; as a result, there is currently an unprecedented need for the use of nucleic acid testing technology. Nucleic acid testing was in extremely high demand during the outbreak; however, it was not adequately satisfied. In fact, the technique of "mix-testing" has been widely used to expedite diagnosis. In this method, various samples are combined into one sample before testing, and, after irregularities are found, individual samples are analyzed [150].

Point-of-care testing has twice been suggested by the Chinese premier as a means of advancing nucleic acid testing. It was obvious that point-of-care diagnostics for nucleic acid analysis could cover this particular gap. Due to the exorbitant expense of this technology and the fact that nucleic acid testing equipment in China was previously primarily imported, China appeared to be particularly unresponsive to serious diseases. In China and other developing nations, the study and creation of low-cost, highly sensitive, quick, and portable nucleic acid testing equipment is now becoming more and more crucial. Many businesses have previously succeeded in creating point-of-care testing tools that could be used to find particular viruses with related kits. The polymerase chain reaction amplification systems GeneXpert, Filmarray, Cobas Liat, and others that were previously offered on foreign stock exchanges were quick and automatic but also expensive and could not be widely used in China. Due to the lack of point-of-care nucleic acid testing devices in China, which was a major factor in the epidemic, the current pandemic has encouraged the development and marketing of domestic point-of-care nucleic acid testing devices such as EasyNAT, Galaxy Nano, boxarray, GenPlex, iPonatic, and AutoSAT [150].

4. Discussion

AI helps the healthcare sector because it lowers the cost of clinical trials by minimizing the amount of time that is lost by human labor in the process of discovering new drugs. By maximizing patient interaction in complex procedures that are complicated by patient concurrent medical conditions and conditions, reimbursement issues, and other environmental and situational conditions, AI solutions can improve the patient encounter above the healthcare factors of clinical protection, medical diagnosis, and therapy options. By intelligently connecting the most important data points, AI may, at the organizational level, optimize healthcare data management. This enables it to support accurate diagnosis, rapid treatment, and preventative measures that enhance health outcomes.

Due to a lack of testing of AI in diagnostic errors, there are problems with data integrity, which is one of the practical hurdles posed by the implementation of AI in the medical industry. In a similar vein, the secrecy, privacy, and complexity of medical data are all increased by the ethical limitations that must be met throughout collection and analysis. The healthcare industry is concerned about ongoing threats of data breaches and cyberattacks due to the sensitive nature of medical data, which can compromise patients' privacy, as well as the various kinds of data that it contains.

Data analysis is one of the uses for which algorithms have promise. There is an enormous amount of data that can be accessed right now, and these data contain the potential to provide information regarding a wide variety of medical and healthcare practices. There are a great many opportunities available now that current computational methods, computer learning, and AI techniques have become more prevalent. For instance, AI makes it simpler to transform data into concrete and actionable insights, which can improve decision making, provide high-quality patient care, adjust to real-time emergencies, and save more lives on the clinical front. Additionally, AI makes it simpler to leverage funds for the development of systems and facilities and to save expenses at the organizational level. In the course of our research on the subject, we came across a number of contributions that discussed various aspects of the problem. One of these aspects was the correctness of the data, which led us to the conclusion that decision makers could benefit from higher data quality. AI methods are a vital instrument for the analysis of data and the extraction of medical insight; furthermore, these methods may be of assistance to medical researchers in their day-to-day work. Therefore, it is necessary for the development of AI applications to ensure that patients have access to all relevant information regarding the technology, and this is a topic that researchers in the future should investigate more.

There is currently a lack of empirical research about the costs incurred and profits realized by healthcare companies that use AI technologies in the sectors of accounting, finance, and leadership. Therefore, research in this area could further improve our understanding of the topic and the number of healthcare organizations that have access to AI-based technology. In the discussion section, it has been noted that further interdisciplinary research is needed to explore the linkages between AI and data quality management as well as the ties between AI and ethical issues in healthcare.

Figure 5 illustrates the theoretical framework that brings together the various aspects that were discussed in the previous section.

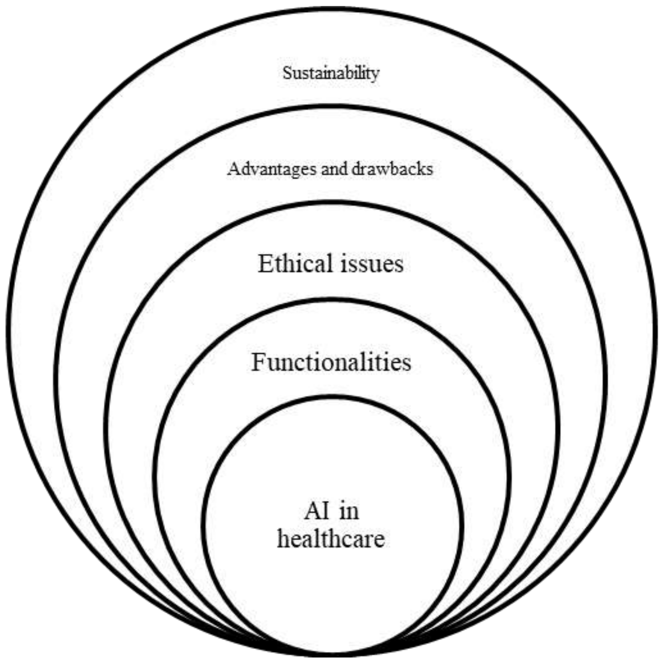

Figure 5. Theoretical framework.

5. Conclusions

The findings of this research indicate that AI and the subfields that fall under its umbrella offer advantages to individuals, companies, and the medical sector. There are some difficulties, such as integrating the data, protecting patients' privacy, resolving legal issues, and maintaining patient safety. According to the findings of this paper, AI can perform a variety of functions, including diagnosis, therapy, the exchange of information, protection, consultation, monitoring, data gathering, and even remote surgery. This paper provides an insight into the present state of AI research as well as its application in the healthcare industry in the real world.

The findings of this investigation are restricted in several ways. To begin, there was a dearth of certain AI operations that could not be accessible. It is common practice for research papers to omit specifics regarding the methods by which AI operates because these features are, for the most part, proprietary in nature. Second, despite the use of an exhaustive search strategy, certain papers on the application of AI in the medical sector were not incorporated into the analysis. To obtain a more nuanced or possibly a more comprehensive grasp of what constitutes benefits, downsides, and sustainable AI in healthcare, future research should take into consideration the possibility of looking for and evaluating studies written in other languages or on other continents.

There is a considerable number of researchers who believe that AI can offer significant advantages to the medical sector, according to the body of literature that was examined for the purpose of this review. However, future researchers will need to carefully analyze the obstacles associated with real and perceived data integrity, as well as the subsequent patient safety and privacy issues that arise from the use of AI in healthcare. This is especially important given the stringent rules that govern the healthcare sector.

Based on the conclusions of this paper, the usage of AI in the medical sector is still quite limited, despite the fact that AI has a wide range of potential applications and advantages. It is therefore possible to do more research on the aspects that have an impact on AI adoption strategies in the healthcare industry. In further research, the topic of how technical, organizational, ethical, data, policy, political, and legal challenges can be effectively reduced ought to be the primary focus. The applications and benefits outlined in this work can be further examined in subsequent studies through the usage of qualitative and quantitative research methods.

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