Adoption of machine learning systems within the health sector: a systematic review, synthesis and research agenda

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Abstract

Purpose – The purpose of this study is to examine the state of research into adoption of machine learning systems within the health sector, to identify themes that have been studied and observe the important gaps in the literature that can inform a research agenda going forward.

Design/methodology/approach – A systematic literature strategy was utilized to identify and analyze scientific papers between 2012 and 2022. A total of 28 articles were identified and reviewed.

Findings – The outcomes reveal that while advances in machine learning have the potential to improve service access and delivery, there have been sporadic growth of literature in this area which is perhaps surprising given the immense potential of machine learning within the health sector. The findings further reveal that themes such as recordkeeping, drugs development and streamlining of treatment have primarily been focused on by the majority of authors in this area.

Research limitations/implications – The search was limited to journal articles published in English, resulting in the exclusion of studies disseminated through alternative channels, such as conferences, and those published in languages other than English. Considering that scholars in developing nations may encounter less difficulty in disseminating their work through alternative channels and that numerous emerging nations employ languages other than English, it is plausible that certain research has been overlooked in the present investigation.

Originality/value – This review provides insights into future research avenues for theory, content and context on adoption of machine learning within the health sector.

Keywords Health sector, Machine learning, Machine learning systems

Paper type Research paper

1. Introduction

Adoption of machine learning (ML) has the potential to significantly alter medical practice by assisting doctors in the investigation of a wide variety of complex data sources. If ML is properly integrated into the intricate healthcare industry, it has the potential to change diagnosis, prediction and the delivery of care (Aldahiri, Alrashed, & Hussain, 2021). For instance, algorithms that use ML are being put to use in the medical field to identify trends and to make predictions (Kourou, Exarchos, Exarchos, Karamouzis, & Fotiadis, 2015). Inputs of data in both organized and unstructured format are also available. When dealing with organized data, worksheets and data sets perform their functions most well. However, data that are unstructured does not have a predetermined organization or structure. Text, audio,

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graphics and recordings can all be difficult to interpret to varying degrees. Up until relatively recently, only those with cognitive talents were able to explore unstructured material. These data are able to be examined and put to use by natural language processing as well as other artificial intelligence (AI) approaches. ML is a branch of AI and computer science focused on data use and algorithms to simulate the approach in which people learn, with the goal of constantly increasing the accuracy of the simulation (El Naqa & Murphy, 2015).

ML has the ability to drastically transform medical practice by supporting clinicians in the examination of complicated and diverse data sources. If ML is successfully integrated into the complex health sector, it has the potential to revolutionize diagnosis, prediction and care delivery. Together, healthcare and technology pioneers are experimenting ML in an effort to alter the status quo. Algorithms and computers are able to sift through massive volumes of data considerably more quickly and correctly than human scientists or medical experts, revealing useful patterns and predictions that may be used to improve illness diagnosis, guide treatment planning and safeguard the public (Greener, Ngiam, & Khor, 2019).

The growing adoption in ML is evident in improving the health sector in areas such as diagnostic, clinical event prediction and the mortality trend prediction. Previous systematic literature reviews on adoption of ML in the health sector have highlighted the following (Abbasgholizadeh Rahimi *et al.*, 2021; Ahmed, Mohamed, Zeeshan, & Dong, 2020; Bravo, 2022; Carriere *et al.*, 2021; Char, Shah, & Magnus, 2018; Elfiky, Pany, Parikh, & Obermeyer, 2018; Kleczyk, Bana, & Arora, 2021; Panesar *et al.*, 2019; Sabry, Eltaras, Labda, Alzoubi, & Malluhi, 2022; Shinozaki, 2019). Firstly, the accumulation of electrical health records has resulted in a meteoric rise in the volume of healthcare data, which has placed an enormous demand on healthcare technology and applications. Secondly, because clinical ML relies on diagnostic data from billions of cases, reliable and adequate data are vital for providing medical recommendations. And, finally, the literature in this area has remained largely fragmented. We argue, therefore, that the growth of literature in this area calls for recall and sense-making. Consequently, there is need to coalesce and synthesis the themes that have been studied and offer an overarching understanding on the adoption of ML systems within the health sector.

Driven by this background from previous studies and in order to stimulate scholarship and offer improved sense of direction, this study offers an inclusive systematic literature review on the adoption of ML within the health sector. In this respect, this research seeks to discourse the following research objectives:

- *RO1.* To examine the status of development of literature on ML systems within the health sector.
- *RO2.* To examine the research trends in the previous studies on ML systems within the health sector.
- *RO3.* To identify future research agenda on ML systems within the health sector.

Piecing these together, this study aims to make sense of what we know on the adoption of ML within the health sector. The aforementioned review provides significant theoretical and empirical advancements by amalgamating preexisting evidence. The study findings reveal that themes such as recordkeeping, drugs development and streamlining of treatment have primarily been focused on by the majority of studies in this area. However, there appears to be less focus by researchers in areas such as precision medicine, clinical decision support systems, predictive analytics and natural language processing. Additionally, challenges like data privacy, algorithm bias and regulatory compliance have been less dealt with. Drawing on our synthesis and interpretation of the study findings, we set out a future research agenda that suggests multiple research guidelines for exploring the theory, content, and context of machine learning (ML) in the healthcare industry.

The article proceeds as follows. In the next section, we review the recent advances in machine learning, the adoption of ML within the health sector in order to build a clearer understanding and theoretically ground the study. Thereafter, the review process and steps utilized to analyze the established articles are highlighted. Next, the results of this review are presented and discussed. Drawing on our synthesis of the findings, we provide suggestions for future research opportunities. Finally, the study limitations and conclusion are made.

2. Recent advances in machine learning

The Generative Pre-Trained Transformer 3 (GPT-3), a language model created by OpenAI, represents a notable breakthrough in the field of ML. This model has the capability to produce text that closely resembles human language, which is a significant development. With a parameter count of 175 billion, this particular model ranks among the most expansive language models developed thus far. The utilization of GPT-3 has been observed across a diverse spectrum of applications, encompassing, but not limited to, language translation, chatbots and text completion, as documented by Ali, Kumar, Alghamdi, Kateb, and Alarfaj (2023). AlphaFold, an artificial intelligence system created by DeepMind, represents a significant advancement in machine learning as it has the capability to forecast the 3D configuration of proteins. With this technology, researchers can understand the fundamental biological processes that underpin disease and develop more targeted treatments (Nussinov, Zhang, Liu, & Jang, 2022).

Reinforcement learning is another area that has seen significant progress lately. The process entails instructing an agent to execute actions within a given environment with the objective of optimizing a reward or outcome. Reinforcement learning has been used in robotics, game-playing AI and other autonomous systems, making it a valuable tool for automating complex tasks (Bangui & Buhnova, 2021). Generative adversarial networks (GANs) are another recent advancement in machine learning. GANs are a class of artificial neural networks capable of producing novel data that exhibit similarities to the original training data. They have been used for image, video and music generation, allowing for more efficient and creative content creation (Sharma *et al.*, 2022).

Transformer networks, a class of neural networks that can process sequential data such as text or speech, have also seen significant advancements recently. With recent advancements, transformer networks have been used for language translation, question answering and text classification, among other applications (Caldarini, Jaf, & McGarry, 2022). Federated Learning has appeared as a promising explanation for privacy-preserving machine learning across decentralized data sources like mobile devices or IoT devices. Using Federated Learning, models can be trained on decentralized data sources while maintaining user privacy, which can help address concerns about data security and privacy (Zhang *et al.*, 2023).

Overall, these recent advances in machine learning demonstrate the potential for the field to have a significant impact on a wide range of domains, including natural language processing, healthcare, robotics and content creation. These advancements point toward trends of more transparent, interpretable and privacy-preserving models that can improve the efficiency and effectiveness of machine learning solutions.

3. Adoption of machine learning in the health sector

Using ML, models have been developed that quickly review data (both structured and unstructured) in order to provide insights. It is reasonable to conclude that ML has helped medical personnel make more informed choices regarding patient diagnoses and treatment alternatives, resulting into an overall enhancement in healthcare services. The following is a breakdown of the application of ML.

3.1 Health archives development and machine learning

Electronic medical records (EMRs) are required for the treatment planning process. EMRs are preferred in ML because of the rich and varied data types they contain. EMRs have a tremendous amount of potential to contribute to the field of biomedical research. However, this promise can only be realized if the data can be mined for applicable medical findings. EMRs were developed to take the place of clinical documentation (Shinozaki, 2019). They were never intended to mine data or achieve anything that paper documents were incapable of doing. The use of EMR, which were initially intended to replace paper files, has resulted in increased costs associated with maintenance, workflow bottlenecks and cybercrime (Samkari & Gutub, 2019). Additionally, research in EMR has contributed to the advancement of biomedical translation (Shinozaki, 2019).

An automated digital assistant called Zuki Health has been designed to help reduce the amount of logistical labor performed by medical professionals (Jabarulla & Lee, 2021). The stress level of healthcare personnel will decrease significantly as a result of the elimination of the requirement for manual data entry.

The deployment of ML in the domain of healthcare and biomedical literature has resulted in a noteworthy application known as text mining. The process entails the recognition and extraction of novel data from unorganized textual information. The methodology entails the application of natural language processing (NLP) techniques to convert unstructured textual information into organized and evaluative data. The utilization of text mining has gained popularity among clinicians and researchers owing to the substantial expansion of accessible information in biomedical literature and electronic health records. The potential uses of this technology encompass a range of tasks such as condensing textual information, retrieving relevant literature and assessing the quality of evidence. The application of ML has been employed to mechanize the screening procedure for systematic reviews, resulting in the identification of pertinent articles and a reduction in workload, thereby enhancing efficiency (Tsafnat, Glasziou, Karystianis, & Coiera, 2018). The application of semantic analysis, which involves the interpretation of meanings from unstructured text, has been utilized for the purpose of extracting information from biomedical literature (Holzinger, 2016).

Johanson and Huang (2022) employed a supervised machine learning methodology to detect individuals with undiagnosed diabetes in primary healthcare settings. A range of algorithms, including decision tree, support vector machine (SVM), random forest and logistic regression, were subjected to testing. The random forest algorithm exhibited superior performance, accurately detecting patients with undiagnosed diabetes.

Zachariah, Rossi, Roberts, and Bosserman (2022) used a ML model based on artificial neural networks (ANN) to compare the treatment suggestions made by medical oncologists and the AI algorithm. The ANN was trained on a data set of breast cancer patients, and the algorithm was able to suggest treatments that were similar to those suggested by the oncologists. This model has the potential to improve treatment recommendations and ultimately patient outcomes.

Hani and Ahmad (2020) conducted a review of several machine learning algorithms that have the potential to detect ischemic heart disease. The authors present a comprehensive summary of various algorithms, including logistic regression, artificial neural networks, decision trees and support vector machines. The utilization of extensive patient data sets to train models has the potential to facilitate the timely identification and prognostication of ischemic heart disease.

Bouvarel and Carrat (2022) used a machine learning model based on gradient boosting to improve mortality risk estimation in intensive care units. The model was trained on a data set of electronic medical records and was able to accurately predict mortality risk in patients. This model has the potential to improve patient outcomes by identifying affected individuals who are at higher risk of mortality and allowing for early intervention.

3.2 Epidemic control and machine learning

Managing pandemic and epidemics has significant socioeconomic consequences. Detecting the zero patient properly and maximizing screening costs are the foundations of expense prevention strategies (Miles, Cockburn, Smith, & Wardle, 2004). As a result, it is important to choose the optimum assessment approach as soon as feasible. van der Schaar *et al.* (2020) reviewed ML approaches, such as supervised and unsupervised approaches, that are used to prevent harmful microbial infections from spreading. Pattern recognition is employed in a model of unforeseen catastrophe, where data from the initial confirmed incidences are used to extrapolate infestations across the demography. When this method is used, the epidemic can be quickly brought under control. Statistics, age and other health conditions might all be included into real-life settings to improve the theory's effectiveness even more (Shinozaki, 2019). If the country's tolerance for the sickness is just temporary, the same technique can be used to prevent re-infections.

Machine learning methods are organized into several groups according on the mathematics they use. Supervised learning, unsupervised learning and reinforcement learning are the three main types of machine learning approaches, according to Dey (2016). If you want your machine to make good predictions, you need to use supervised learning, which requires a labeled training data set that you provide to it in advance (Dey, 2016). Algorithms like the decision tree (DT), naive Bayes (NB) and support vector machine (SVM) are often used in supervised machine learning (ML).The review adds significantly to theory and research by bringing together previously scattered pieces of information. Wiens (2016) posits that unsupervised learning constitutes a form of machine learning that operates independently of annotated data and is predominantly utilized to arrange and systematize data, rather than for the purpose of categorization. In the discipline of machine learning, reinforcement learning is a computational approach in which an agent learns to make choices in response to a reward signal from its environment. The agent's objective is to maximize its long-term benefit by making decisions that will lead to the best possible outcomes (Marinescu, Dusparic, & Clarke, 2017).

Ensemble learning is a prevalent ML technique that involves the amalgamation of multiple classifiers to execute a single prediction task, as posited by Dilsizian and Siegel (2014). Ensemble learning is a widely employed technique in which multiple weak classifiers are combined to form a strong classifier. Boosting is a prominent example of such an approach. Neural networks are complex mathematical constructs that comprise of an input layer, an output layer and one or more hidden layers sandwiched between them. Each layer undergoes a sequence of computations, resulting in enhanced efficiency. The area of study concerned with neural networks, which are characterized by their multilayered structure, is commonly referred to as deep learning. Neural networks can be catalogued into three main groups, namely supervised, unsupervised or reinforced.

3.3 Machine learning and surgery

Despite having such a solid base in scanning and mapping, ML was only recently brought into the area of surgery (Crowson *et al.*, 2020). Nevertheless, new systems are focusing on feature detection and software management both through pre-operative and cross-functional/cross guiding. The computerized surgical excision, postoperative process planning, augmentation of robotically assisted supplies and laparoscopic quality evaluation are all examples of microsurgery (Porpiglia *et al.*, 2020). Even though it is too soon to talk about machines performing all procedures, they are already helping practitioners manipulate endoscopes, predict infections and diagnose disorders using radiography and pathology (Char *et al.*, 2018).

The utilization of ML within the healthcare industry has garnered considerable attention as a result of the copious quantities of data produced by the system on a daily basis (Dash, Shakyawar, Sharma, & Kaushik, 2019). Beam (2018) asserts that machine learning possesses the potential to identify notable associations within vast data sets generated by the healthcare sector and construct computational models that provide accurate predictions. The utilization of machine learning (ML) for predicting the probability of nosocomial infection has been demonstrated by Wiens, Horvitz, and Arbor (2016) through the extraction of data from electronic health records. A mathematical algorithm, known as a machine learning classifier, is assigned the responsibility of recognizing patterns and generating predictions based on a provided dataset. The resulting output of this algorithm is known as a machine learning model. A machine learning model encompasses the entirety of the learning procedure, comprising both the algorithm's training and the employed feature set.

The health sector is increasingly utilizing machine learning techniques as they possess the capability to analyze extensive data sets and identify patterns that may not be discernible to human experts. The utilization of these patterns can facilitate the provision of individualized healthcare, prognosticate patient prognoses, recognize individuals at elevated risk and implement preemptive interventions. The study conducted by Jaotombo *et al.* (2020) employed machine learning techniques to forecast unplanned rehospitalization within a 30-day period. The research utilized a vast medico-administrative database in France for this purpose. The research revealed that the machine learning models attained a notable level of precision in forecasting rehospitalization, thereby presenting a potential avenue for enhancing patient care through the association of persons who are at a higher risk of necessitating additional medical attention. The authors Min, Mobahi, Irvin, Avramovic, and Wojtusiak (2017) devised an ML approach guided by ontology to forecast the performance of daily living tasks among individuals with cancer. A systematic review of this nature would hold significant importance in steering future machine learning research endeavors that strive to enhance the dissemination of pertinent evidence to the point of care. Table 1 provided summary of the various ML techniques and the medical field in which these are applied.

Machine learning has the capability to detect significant correlations within extensive data sets generated by the healthcare industry. The utilization of electronic health records data has been employed to forecast the likelihood of nosocomial infection. The ML field in the healthcare sector has seen a proliferation of studies, yet the literature remains fragmented. In response, this paper aims to consolidate existing research by conducting a comprehensive review, synthesizing key insights and providing a clearer direction for future scholarly endeavors.

4. Review methodology

This review followed a systematic literature review approach (Okoli & Schabram, 2010) to develop a comprehensive understanding on the status as well as gaps in literature on machine learning within the health sector. The systematic review employed a methodical approach to identify, amalgamate and assess literature that was published from 2012 to 2022. The methodology presented offers a systematic and replicable approach to categorizing, screening, evaluating and presenting publications, which can be attributed to its consistent application. This ensured the transparency of the procedures and the credibility of the results.

ML technique	Medical field applied	Illustrative reference
Supervised learning	Unrecognized diabetes detection	Johanson and Huang (2022)
	Ischemic heart disease detection	Hani and Ahmad (2022)
	Mortality risk estimation in intensive care units	Bouvarel and Carrat (2022)
Unsupervised learning	Text mining, literature retrieval	Ahmed, Mohamed, Zeeshan, and Dong (2020)
	Development of EMRs	Shinozaki (2019)
Reinforcement learning	Pandemic control and management	van der Schaar *et al.* (2020)
Ensemble learning	Nosocomial infection prediction	Wiens *et al.* (2016)
Neural networks	Breast cancer treatment suggestions	Zachariah *et al.* (2022)
	Surgery, endoscope manipulation, radiography diagnosis	Char, Shah, and Magnus (2018)
	Microsurgery, laparoscopic quality evaluation	Porpiglia *et al.* (2020)
	ML in postoperative process planning	Crowson *et al.* (2020)
Generative pre-trained transformer 3 (GPT-3)	Language translation, chatbots, text completion	Ali *et al.* (2023)
AlphaFold	Protein structure prediction, targeted treatment development	Nussinov, Zhang, Liu, and Jang (2022)
Reinforcement learning	Robotics, game-playing AI, autonomous systems	Bangui and Buhnova (2021)
Generative adversarial networks (GANs)	Image, video and music generation	Sharma *et al.* (2022)
Transformer networks	Language translation, question answering, text classification	Caldarini, Jaf, and McGarry (2022)
Federated learning	Privacy-preserving machine learning on decentralized data sources	Zhang *et al.* (2023)

Source(s): Authors' elaboration

Table 1. Summary of ML techniques applied in medical field

A coding framework was devised to facilitate the delineation of the information source, methodologies utilized and pertinent data extracted from extant literature.

4.1 Data source and search strategy

A variety of search databases (National Library of Medicine, PubMed, and Google Scholar) were used to identify the articles. To retrieve relevant literature, the Boolean operators alongside the following search strings were in use:

Str1: ("Machine Learning" OR "Machine learning system*") AND ("Health sector*" OR "Healthcare")

Str2: "Machine Learning" AND (Adoption OR Application*) AND (Health OR "Health Sector*")

Based on the search string, a total of 1108 articles were identified (National Library of Medicine = 228, PubMed = 93, Google Scholar = 787).

4.2 Screening

The subsequent inclusion and exclusion criteria were utilized:

(1) Appropriate for the related studies, which are centered on the adoption of ML within the health sector

(2) Peer-reviewed journal articles and book chapters

(3) Language – English

(4) Publication time frame – 2012–2022

The association and selection of appropriate publications that were utilized in this study are summarized in Figure 1. After the eligibility of the articles had been determined by using the inclusion and exclusion criteria, 28 qualifying papers were included in this review analysis.

4.3 Data extraction process

An in-depth qualitative investigation was carried out on the chosen publications. A coding framework was developed to help with the data extraction process. Four categories for classification were used based on the goals of this study's research (Massaro *et al.*, 2015).

(1) Research method used

(2) Thematic issues/study focus area

(3) Journal, author(s) and year of publication

(4) Study location

The extraction form was independently piloted by two reviewers using 6 systematic reviews. For this piloting process, 3 PubMed and 2 Google Scholar reviews were used that were not part of the sample of reviews included in the analysis. From the results, nothing was reported to be unclear or inconsistent. Data inconsistencies and bias were decreased by having the authors independently carry out data extraction using the coding framework. Figure 2 provides a summary of the data extraction framework that was used in the study.

5. Results

The first two research objectives are addressed in the following sections.

RO1. To examine the status of development of literature on ML systems within the health sector.

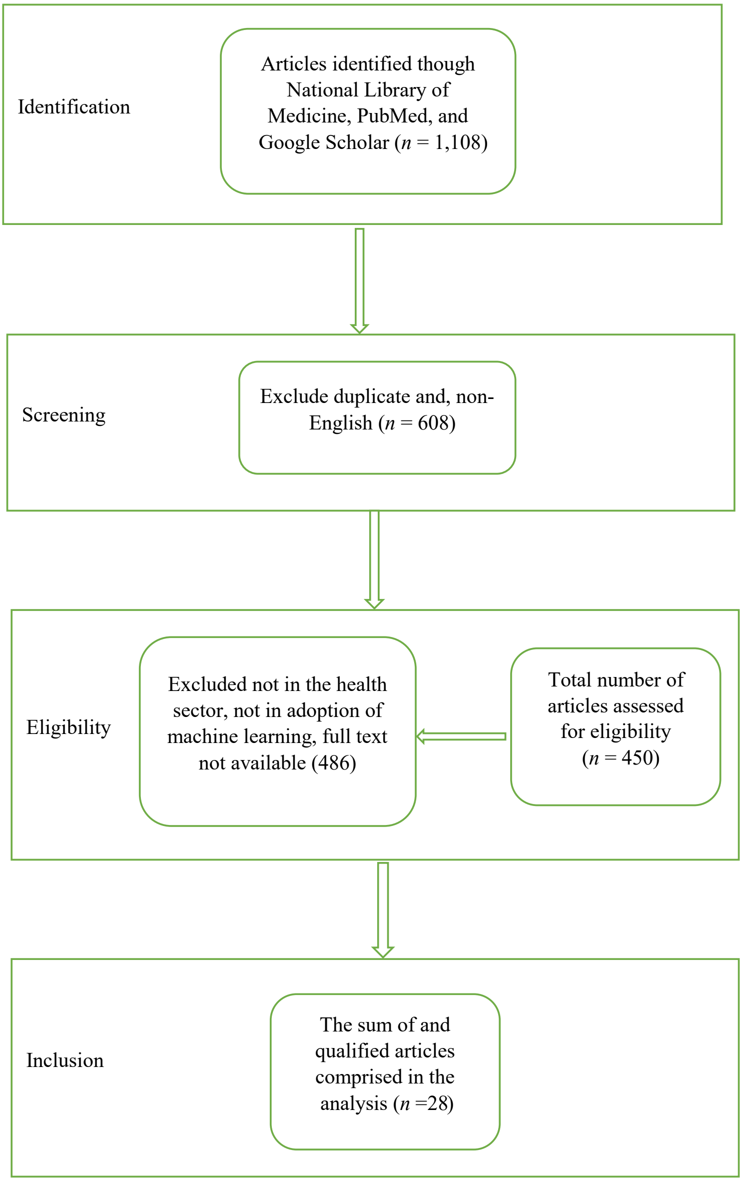
RO2. To examine the research trends in the previous studies on ML systems within the health sector

5.1 Development of literature

In this section, we present the results to the first research question. Our goal in formulating this research topic was to get an understanding of the current state of the literature around the use of ML systems in the healthcare industry. To investigate this, we looked at the number of publications that appeared each year over the study period considered in this research (2012–2022) and the citation scores of these publications.

A total of 28 articles were found to exist in the study period. As shown in Figure 3, the total number of articles varied from one year to the other during the time period under consideration. Publications peaked in, and were most numerous in 2014, 2018, 2020 and 2021.

Progress seems to have been sporadic during the time period under examination. Considering the vast potential of ML in healthcare, this does suggest that researchers have devoted less attention to this field. Additionally, it seems from a survey of the published works that most authors have tended to publish in the more prominent scientific journals. The 28 articles comprising this review are presented in Table 2.



Source(s): Authors' elaboration

Figure 1. Summary of review process

5.2 Research trends observed

The health sector is increasingly benefiting from the utilization of machine learning techniques, which possess the capacity to scrutinize extensive data sets and identify patterns that may not be discernible to human specialists. The utilization of these patterns can facilitate the provision of tailored healthcare, prognosticate patient prognoses, pinpoint

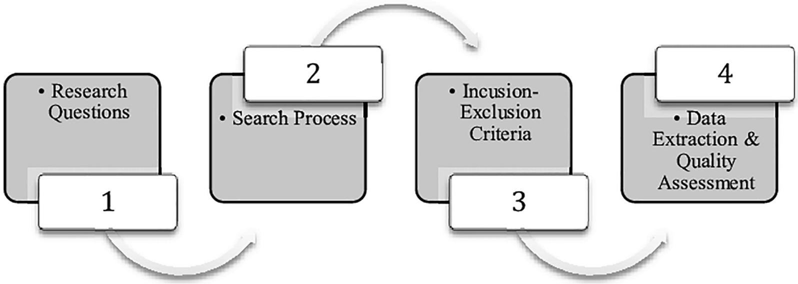


Figure 2.
Data extraction process

Source(s): Adapted from Halim *et al*. (2015)

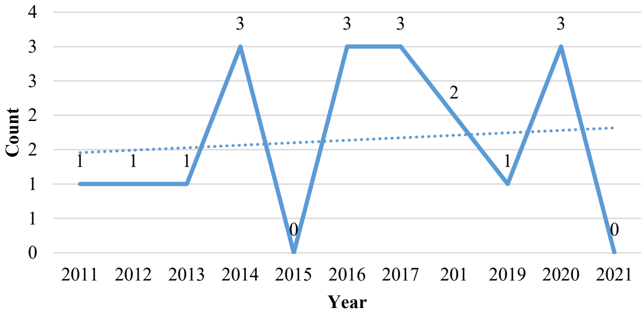


Figure 3.
Publications by year

Source(s): Authors' elaboration

individuals with elevated risk and implement preemptive interventions. The study conducted by Jaotombo *et al.* (2020) employed machine learning techniques to forecast unplanned rehospitalization within a 30-day period. The researchers utilized a vast medico-administrative database in France for this purpose. According to the research, the machine learning models demonstrated a notable level of precision in forecasting rehospitalization and have the potential to enhance patient care by pinpointing individuals who are at a higher risk of necessitating additional medical attention. The authors Min *et al.* (2017) devised a machine learning approach that was guided by an ontology to forecast the performance of daily living tasks among individuals with cancer. The study demonstrated the potential for ML to assist in assessing patient needs and supporting clinical decision-making in cancer care.

Vitorasso and De Souza Ribeiro Vitorasso (2020) provided an overview of ML applications in health-related areas, highlighting both opportunities and potential pitfalls. The authors noted that ML has the potential to revolutionize healthcare by improving diagnosis, predicting risk and even facilitating personalized medicine. However, they also highlighted the importance of maintaining data privacy and ethical considerations when implementing ML in healthcare. Shouval *et al.* (2017) relied on machine learning to predict 30-day mortality through data mining, from the acute coronary syndrome. The study demonstrated that ML models could accurately predict mortality risk and could be useful for clinical decision-making.

Dias, Gupta, and Yule (2019) explored the use of ML to assess physician competence. They developed an ML model that could identify areas where individual physicians need additional training and support, demonstrating the potential for ML to revolutionize medical education and training. Overall, the use of ML techniques in healthcare has the potential to improve patient

Author	Title	Journal	Citation index
Abbasgholizadeh Rahimi *et al.* (2021)	Application of Artificial Intelligence in Community-Based Primary Health Care: Systematic Scoping Review and Critical Appraisal	*Journal of Medical Internet Research*	5
Ahmed *et al.* (2020)	Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine	*Journal of biological databases and curation*	171
Bray *et al.* (2018)	Global cancer statistics	*Cancer Journal for Clinicians*	17378
Cutillo *et al.* (2020)	Machine intelligence in healthcare—perspectives on trustworthiness, explainability, usability, and transparency	*Npj Digital Medicine*	71
Elfiky, Pany, Parikh, and Obermeyer (2018)	Development and Application of a Machine Learning Approach to Assess Short-term Mortality Risk Among Patients With Cancer Starting Chemotherapy	*JAMA Network Open*	78
Faust *et al.* (2018)	Automated detection of atrial fibrillation using long short-term memory network with RR interval signals	*Computers in Biology and Medicine*	171
Jordan and Mitchell (2015)	Machine learning: Trends, perspectives, and prospects	*Science*	2
Kazantsev, Ponomareva, Kazantsev, Digilov, and Huang (2012)	Development of e-health network for in-home pregnancy surveillance based on artificial intelligence	*International Conference on Biomedical and Health Informatics*	
Khanna, Sattar, and Hansen (2013)	Artificial intelligence in health–the three big challenges	*The Australasian medical journal*	315
Kleczyk, Bana, and Arora (2021)	Leveraging Advanced Analytics to Understand the Impact of the COVID-19 Pandemic on Trends in Substance Use Disorders	*Addictions - Diagnosis and Treatment*	0
Ma and Tavares (2015)	A Novel Approach to Segment Skin Lesions in Dermoscopic Images Based on a Deformable Model	*Journal of Biomedical and Health Informatics*	142
Quinn, Jacobs, Senadeera, Le, and Coghlan (2022)	The three ghosts of medical AI: Can the black-box present deliver?	*Artificial Intelligence in Medicine*	15
Schirrmeister *et al.* (2017)	Deep learning with convolutional neural networks for EEG decoding and visualization	*Deep Learning*	1367
Sun (2021)	Adopting Artificial Intelligence in Public Healthcare: The Effect of Social Power and Learning Algorithms	*International Journal of Environmental Research and Public Health*	0
Tuli *et al.* (2020)	An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments	*Future Generation Computer Systems*	299

(*continued*)

Table 2.
Papers in the review

Author	Title	Journal	Citation index
Vamathevan *et al.* (2019)	Applications of machine learning in drug discovery and development	*Nature reviews drug discovery*	463
Ziuziański, Furmankiewicz, and Sołtysik-Piorunkiewicz (2014)	E-health artificial intelligence system implementation: case study of knowledge management dashboard of epidemiological data in Poland	*International Journal of Biology and Biomedical Engineering*	8
Dilsizian and Siegel (2014)	Artificial intelligence in medicine and cardiac imaging: harnessing big data and advanced computing to provide personalized medical diagnosis and treatment	*Current cardiology reports*	16
Bae, Lim, Kwon, and Nauck (2021)	Development of deep learning-based CT scoring system for COVID-19 pneumonia: Meta-analysis and validation study	*PLoS ONE*	2
Chen, Yu, Cheng and Hao (2019)	A Deep Learning Approach to Predict Clinical Outcomes from Electroencephalography in Critically Ill Patients	*Anesthesiology*	8
Davenport and Kalakota (2019)	Machine learning for healthcare: a review	*Physiological Measurement*	265
Garrido-Mesa, Adams, Gálvez, and Garrido-Mesa (2022)	Machine learning-based tools for healthcare personnel selection: systematic review	*Journal of Medical Systems*	0
Kivrak, Shah, and Chu (2021)	Comparison of deep learning techniques for COVID-19 detection using chest X-ray images	*PeerJ Computer Science*	0
Kumar *et al.* (2018)	Development of machine learning algorithms for prediction of impending fractures in patients with metastatic cancer to the spine	*European Spine Journal*	30
Li *et al.* (2021)	An intelligent edge computing system for data privacy protection in healthcare	*IEEE Access*	2
Müller (2016)	Automatic localization of anatomical landmarks in medical images using an anatomical atlas-based approach	*Medical Image Analysis*	189
Narain *et al.* (2021)	Artificial intelligence for predicting diabetic retinopathy progression: A systematic review	*EClinicalMedicine*	0
Zhang *et al.* (2021)	Deep Learning Predictive Analytics for Inpatient Glycemic Control	*Journal of Diabetes Science and Technology*	0

Table 2.

Source(s): Authors' elaboration

outcomes dramatically. However, it is essential to ensure these technologies are implemented within the ethical and legal framework to maximize their benefits and minimize harm.

Overall, the following themes can be highlighted from the works reviewed in this study:

5.3 Records keeping

In 2017, Schirrmeister proposed novel techniques for representing the characteristics of deep learning through the utilization of convolutional neural networks (ConvNets). It was observed that ConvNets acquire the ability to employ a diverse range of power in the alpha, beta and high gamma frequencies. The research employed a qualitative approach that utilized a case study methodology. Furthermore, the research pertains to the development of convolutional neural networks (ConvNets) utilized for information decoding, specifically in the context of analyzing unadorned electroencephalogram (EEG) data without any manually engineered features. Convolutional neural networks (ConvNets) are advantageous due to their capacity to facilitate end-to-end learning and their ability to scale effectively for large data sets. However, one of its limitations is that it has the potential to generate inaccurate predictions and necessitates the utilization of training data.

The use of natural language processing (NLP) algorithms to extract information from unstructured text is illustrated in the context of electronic health records (EHRs). For example, an NLP algorithm may be used to extract clinical features and diagnoses from a doctor's notes, and then it can organize those findings in a logical fashion (Jordan & Mitchell, 2015). It is possible that this is a list of diagnoses for a particular patient, or it might be a sequence of treatments that have to be administered in a certain order. This led to the development of artificial intelligence medical aid.

5.3.1 Drugs development. The process of finding and developing new medicines is lengthy, convoluted and highly variable. When applied to well-defined problems with large amounts of high-quality data, the tools available via ML may enhance discovery and decision-making (Vamathevan *et al.*, 2019). All areas of drug research have opportunities for ML applications. Clinical trial examples include target validation, biomarker discovery for prognosis and digital pathology data processing. There has been a wide variety of contexts and techniques to applications, with some producing reliable forecasts and insights. It may be difficult to put ML to use since the findings it produces are difficult to explain and reproduce (Forest & Martin, 2018). High-dimensional data that are both systematic and comprehensive are still lacking in every field. Applying ML possesses the capability to expedite the drug discovery and development process while simultaneously reducing the incidence of unsuccessful outcomes, particularly if attempts to address these difficulties continue and more people become aware of the components required to validate ML techniques (Vamathevan *et al.*, 2019).

As a result of doctors' increased understanding of the molecular and genetic structure of a patient, and, for instance, a tumor research (Elfiky *et al.*, 2018) can be extended to include ML to enable simulations on computers rather than testing in live situations. In order to identify essential individuals for the purpose of pharmaceutical review and analysis, these computers are able to handle hundreds, if not millions, of simulations. Drug discovery models that are enabled by ML might save years or even decades off of the design process, and hence lowering the overall cost of manufacturing medication and shortening the amount of time it takes to treat a patient (Kleczyk *et al.*, 2021).

Syndrome differentiation is a fundamental aspect of Chinese medicine utilized for the treatment of infectious fever, as noted by Ma and Tavares (2015). The complexity of distinguishing between infectious fever syndromes poses a significant challenge for traditional classical Chinese medicine. The integration of deep learning presents a promising approach for distinguishing computer-assisted syndrome of infectious fever. The proposal entails incorporating an adaptive dropout mechanism within the stacked auto-encoder. The strengths of this study are deemed to be the reduction of overfitting and the improvement of classification and accuracy.

All areas of drug research have opportunities for ML applications. Examples include target validation, biomarker discovery for prognosis and digital pathology data processing. High-dimensional data that are both systematic and comprehensive are still lacking in every field. Drug discovery models that are enabled by ML might save years, or even decades, off of the design process.

5.3.2 Automated records. The increasing prevalence of cloud computing systems has been beneficial to the development of ML technologies that mine enormous amounts of data in order to identify flaws in the functioning of existing systems and to offer alternative approaches to the resolution of challenging problems. Because it has the potential to improve the services provided, many stakeholders in the healthcare industry have urged for the utilization of ML technology (Greene & Cross, 2017). Access to data, the collection of symptoms associated to patients and the transmission of relevant remedies are the primary tasks that require the most integration of ML in the industry.

The authors Tuli *et al.* (2020) introduced a novel approach called HealthFog, which employs deep learning techniques for the automated detection of heart diseases. HealthFog provides a cost-effective, fog-based solution and streamlined data management for individuals with cardiac conditions, utilizing a diverse range of medical devices. The benefits of a novel HealthFog computing paradigm encompass energy-saving solutions and low-latency data processing solutions. Regarding the limitations of fog computing in medical applications, it is vital to have an inclusive understanding of the response and latency time. Additionally, optimizing the parameters of quality of service (QoS) in real-time Fog environments can be challenging.

5.3.3 Streamlining treatments. The study conducted by Bray *et al.* (2018) delved into the utilization of advanced reinforcement learning models in the context of computer-assisted diagnosis and treatment of lung cancer. The investigation was carried out utilizing an extensive array of scientific databases as sources of reference, thereby enabling the retrieval of a wide range of publications in the relevant field. At present, lung cancer represents a significant peril to the human population. A considerable number of individuals experience the presence of two distinct categories of tumors within their pulmonary system, namely benign and malignant. Deep reinforcement learning models have demonstrated the capability to accurately detect lung tumors and produce reliable results. The primary obstacle in employing deep reinforcement learning models for the treatment of lung cancer lies in the formulation of an effective function for updating the Q-value of each action. Melanoma is a malignant form of skin cancer that poses a significant threat due to its high propensity for metastasis. There exist three distinct categories of melanocytic lesions, namely common nevi, atypical nevi and melanomas. Bray *et al.* (2018) employed an Internet of Things (IoT) technology-driven system to classify skin lesions. The method under consideration employs convolutional neural network (CNN) models to obtain images from the ImageNet dataset. The advantages of this approach include its versatility across various domains and its user-friendly nature. The study's limitation pertains to the issue of internet accessibility. The process of interfacing with an Application Programming Interface (API) within the context of Learning to Interpolate for Data Augmentation (LINDA) and transmitting images necessitates a reliable connection, which may pose difficulties in areas with inadequate network coverage.

According to Sarraf and Tofighi (2016), recent advancements in automated electroencephalography (EEG) disease diagnosis and detection systems can be attributed to the utilization of machine learning (ML) techniques. One advantageous aspect of this survey is the potential for improved EEG decoding performance through the utilization of automated feature extraction capabilities. Furthermore, the identification of atypical medical conditions can be achieved by means of evaluating their electroencephalogram. The accessibility of EEG pathology data sets presents a potential obstacle – while some of these data sets are accessible through online means, a significant proportion of them are limited in size and may not be suitable for certain machine learning models, as noted by Kamnitsas *et al.* (2017). Cerebral vascular accidents (CVA), commonly known as stroke, is a medical condition characterized by the cessation of certain brain functions due to either ischemic or hemorrhagic events (Holzinger, 2016). In the majority of instances, it can result in mortality.

Rapid and accurate diagnosis can effectively address this matter. Computed tomography (CT) and magnetic resonance imaging (MRI) are regularly employed modalities for the purpose of diagnosing strokes.

Bolhasani, Mohseni, and Rahmani (2021) have proposed the utilization of an IoT framework for the sorting of stroke based on CT images. This involves the deployment of convolutional neural networks (CNN) to discern the health status of the brain, identify whether the stroke is ischemic or determine if it occurred due to bleeding. The utilization of IoT in the healthcare sector offers the benefit of reduced reliance on human intervention, thereby resulting in a decrease in the occurrence of human errors. According to Kulkarni, Gawali, and Kharat (2021), it is not feasible to implement the proposed framework in other medical imaging modalities, despite the need for its expansion. This constraint is an intrinsic aspect of the evaluation process.

In their study, Faust *et al.* (2018) constructed a machine learning (ML) model utilizing long short-term memory (LSTM) architecture. The model was designed to uncover atrial fibrillation (AF) episodes by analyzing heart rate (HR) signals. A pilot study was conducted on 20 participants using a machine learning long short-term memory (LSTM) system. The system was trained and tested on labeled heart rate (HR) signal data obtained from the Atrial Fibrillation Database (AFDB) provided by Physio Net. In contrast to alternative machine learning methodologies, the accomplishments of this particular model are comparatively less constrained. Additionally, it is possible to extrapolate information obtained from a limited data set to a more extensive data set. The deficiency of this work lies in the omission of the crucial aspect of training.

6. Discussion

The third research objective of the study is discussed in this section.

RO3. To identify future research agenda on machine learning systems within the health sector.

In addressing this question, we draw attention to potential avenues for advancing the state of the art in the application of machine learning to the healthcare industry.

Technology-enabled healthcare is gradually becoming a reality as the prevalence of smart medical devices increases. The future of ML in healthcare is highly bright since the healthcare industry supports innovation. The technology is responsible for analyzing large amounts of data, making reliable predictions about potential outcomes and carrying out a number of other tasks. A customized medication regimen may be developed using this for patients with very specific conditions. This ML method may someday be used in tandem with nanotechnology to enhance drug delivery. ML is useful since it can solve the present problem and foresee potential future challenges. The ML system can also predict global pandemics. In today's environment, the expert must bring a vast quantity of data under control from sources such as website data and real-time social media updates. Using this technology, we can better confirm these numbers and anticipate the spread of illnesses both big and small.

Additionally, continuous education is necessary for the use of automated programs and services (Orekhova, Romashkova, & Gaidamaka, 2020). The human population being varied, there are some who might be comfortable with modern technology, while others may not. It is possible that the elderly and the terminally sick, who are thought to benefit the most from telehealth innovations, may be unable to make use of these new tools. There is need to make sure that the use of ML does not widen the digital gap, but rather enables us to deliver top-notch, patient-centered healthcare to everyone. In the same vein, medical professionals need ML training before it can be used effectively in healthcare settings (Orekhova *et al.*, 2020).

Finally, ML is only a tool for improving people's health (Sun, 2021). Incorporating ML into healthcare has always been seen more as a process than a goal; but as healthcare continues to be digitalized, the line between the two is clearer than ever before. Healthcare professionals should acquire ML knowledge, come to terms with its usefulness and take a realistic approach to designing and implementing automation solutions (Jabarulla & Lee, 2021).

In summary, the findings of this review are relevant to medical practitioners, researchers and policymakers in healthcare and ML. Medical practitioners and researchers may use these findings to strategically incorporate ML into their systems to achieve more in the medical field. Researchers can use this study as a source of literature in future studies. Additionally, policymakers might find the findings useful in informing them on new policy directions. The setting of electronic health records is used to demonstrate how natural language processing (NLP) algorithms may be used to extract information from free-form text. Extracting clinical characteristics and diagnoses from a doctor's notes, for instance, may be done with the help of an NLP algorithm. This might be a list of diagnoses for the patient, or it could be a treatment protocol that must be followed in a certain order.

In the case of drug development, ML-enabled models might potentially cut down the design time by a decade or more. Validation of targets, connection of prognostic biomarkers and examination of digital pathology data are all examples (Vamathevan *et al.*, 2019). Systematic and all-encompassing high-dimensional data are still absent in every discipline.

7. Limitations of the review

The present investigation exhibits certain constraints in its methodology. The search was limited to journal articles published in English, resulting in the exclusion of studies disseminated through alternative channels, such as conferences, and those published in languages other than English. Considering that scholars in developing nations may encounter less difficulty in disseminating their work through alternative channels and that numerous emerging nations employ languages other than English, it is plausible that certain research has been overlooked in the present investigation. Notwithstanding these constraints, the present study offers a thorough and methodical survey of machine learning frameworks in the healthcare domain and identifies significant deficiencies in the present literature that can guide future research endeavors. The presented findings are anticipated to be of significance to fellow scholars and practitioners operating in a field that evidently necessitates further scrutiny and dedication from researchers to attain full development.

8. Concluding remarks

Numerous forms of ML will soon find their way into cutting-edge healthcare systems. It is this skill that laid the groundwork for molecular diagnostics (Ahmed *et al.*, 2020), which is now widely acknowledged as a welcome advancement in treatment. For ML systems to become widely used, there is need for such systems to be sanctioned by regulatory bodies, incorporated into EHR mechanisms (Abbasgholizadeh Rahimi *et al.*, 2021), so that comparable products perform similarly, taught to clinicians, revised in the research area over time and have their diversity integrated without any dispersion in both developing and underdeveloped countries. It is only then that they will be able to compete with more established forms of medical diagnosis and therapy.

When it comes to patient care, ML is being put to good use. The efficiency gains from using ML are beneficial for both patients and clinicians in a variety of ways. Medical billing and coding automation, together with clinical management and treatment recommendation generation, are some of the most widespread uses of ML today. Telemedicine, drug discovery and robotic medical assistants are just a few of the areas where ML is being actively studied and developed at the moment. It is very likely that in the near future, ML methods will be widely used in the medical area, simplifying the lives of patients and doctors alike. Nevertheless, several aspects for adaptation must also be examined.

One of the practical implications for this paper is that policymakers can use the synthesized evidence to substantiate the critical need for ML within the health sector. Non-technical researchers might profit from investigating the incorporation of ML in other areas other than the ones covered in this study. ML has widespread use in the realm of scientific inquiry. Its value has increased as a tool for processing large amounts of data and making reliable predictions to aiding scientists in their quests for knowledge. This study also evidenced less focus by researchers in areas such as precision medicine, clinical decision support systems, predictive analytics and natural language processing. Future research could focus more on such areas to help grow the body of knowledge on ML within the health sector. Additionally, challenges like data privacy, algorithm bias and regulatory compliance have been less dealt with, and more studies around this are called for.

In closing, we argue that ML has already begun to revolutionize the healthcare industry, and its potential impact is only expected to grow in the future. As more data become available and algorithms become more sophisticated, we can expect to see even greater advances in the diagnosis, treatment and prevention of diseases and conditions.

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