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REVIEW ARTICLE

Applications of Artificial Intelligence for Health Informatics: A Systematic Review

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ABSTRACT

Health informatics (HI) is a multidisciplinary field that involves the application of information technology, data analytics, and artificial intelligence (AI) to healthcare. AI has revolutionized the field of HI, providing new tools and approaches for managing and analyzing HI data to improve patient care, research, and administration. Health information systems, clinical pictures, and sophisticated language that is complex, difficult to understand, and mostly unstructured have all been used in the present study. The emergence of AI applications and their integration with healthcare systems have significantly contributed to the proliferation of unorganized and unstructured data, which further complicates the research process. This research conducts a thorough evaluation of HI to enhance AI applications. We examine the present level of AI applications in HI, concentrating on how AI affects participatory health from the viewpoints of both patients and clinicians. Our review highlights the competency domains of HI, including information technology, health information systems, telemedicine and m-Health, health information security and privacy, consumer HI, and clinical informatics. We also found that AI gives social media and mobile apps a new element and that AI statistical analysis may be used to duplicate or improve the individualized medical advice provided by healthcare experts, diagnose rare and complex conditions, predict adverse health events, and more. With the help of AI, HI professionals can extract strong intelligence from online resources to better understand patient needs and behaviors ultimately leading to improved patient outcomes. This comprehensive assessment sheds important light on the status of AI applications in HI today and identifies key areas for further study and advancement.

1. INTRODUCTION

Health informatics (HI) is the information technology and healthcare intersection. It includes the use of technology to manage and analyze healthcare data to enhance patient care, research, and administration. This can include electronic health records (EHR), telemedicine, and communications technology systems [1,2]. The HI sector has several competency domains such as information technology, consumer HI, m-Health and telemedicine, health information security, health information systems, and clinical informatics, as shown in Figure 1. HI professionals work in a variety of roles, such as data analysts, systems administrators, and clinical informaticists, to ensure technology is used effectively and safely in the health sector [3]. A personal digital assistant (PDA), a mobile phone, a patient monitoring device, or other wireless devices can be used to access a patient's medical information in the context of HI, which is an industry that uses artificial intelligence (AI) to advance the domains of medicine and public health. Therefore, using the AI technique, we developed a variety of healthcare-related applications that provide numerous details information about health. Currently, there are lots of HI projects underway, and there are approximately 40,000 medically related applications available globally [4].

Recently, in HI fields, there have been numerous proposals and reviews and the utilization of AI in healthcare. The use of AI in HI has been effectively proven for maintenance purposes and has enhanced the evaluation of healthcare records. The participatory health paradigm, which allows individuals to gather, record, and monitor markers of their health in numbers and get information about their general health, is shown by the quantified self-movement [4]. Though undoubtedly revolutionary, technical advancements in intelligent computing and analytical techniques, including AI, are now making it possible to get a greater knowledge of one's health [5]. This is especially

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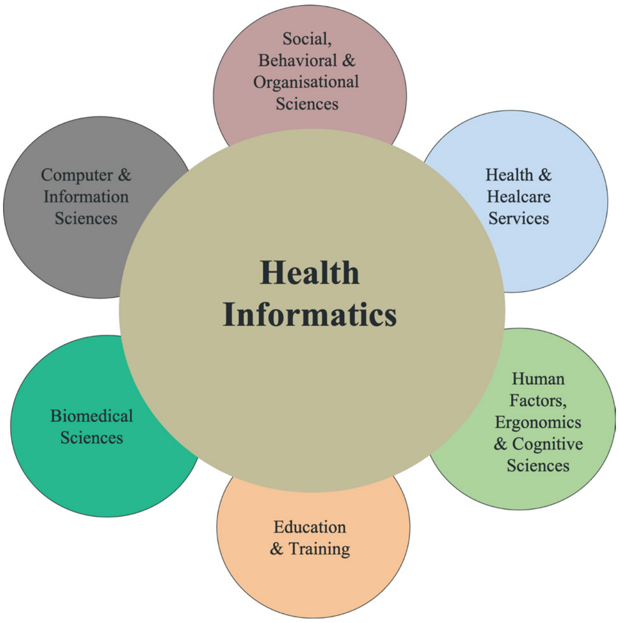

Figure 1 | Key domains of knowledge in health informatics.

important given that individuals may now gather more kinds, of data, and data of higher quality, on themselves and their health.

Because of AI approaches and processes, people and professionals working in cooperative medical informatics are given the opportunity to obtain substantial knowledge from internet sources [6]. AI gives technologies such as mobile apps and social networking sites a different dimension toward the goals of participative health. For example, using AI computational modeling may be utilized to complete a range of activities. such as reproducing or improving the customized medical advice provided by healthcare experts; detecting unusual and difficult disorders; understanding how epidemics or diseases spread; foretelling unfavorable health outcomes; and learning how individuals utilize healthcare. and comparing experiences with the results from different treatments [7–9]. Even though AI provides a positive and creative method to enhance participatory health, the subject is still developing, especially in terms of solid empirical findings. This study examines the effects of AI applications on the HI industry. Both from the standpoint of the patient and the practitioner, participatory health has a wide range of applications.

Motivations and scope: Many articles on HI and applications in the field of HI, AI, and the big data analytics industry have been presented as reviews. A comprehensive, systematic study of AI applications in the HI sector is not yet available. The evaluations that already exist are either narrowly focused on a particular aspect of HI, such as clinical decision support [10,11], Evidence-based healthcare [12–15], Celiac disease [16], digital health [17,18], big data analytics [19–21], or the application and performance of AI algorithms [22–26]. Some studies focused on specific diseases (cardiovascular disease [17], celiac disease [16], and breast cancer identification and diagnosis [27]). There is no study to our knowledge that encompasses the whole scope of research that has been done in this field. With the exception of a few articles [28–32], these studies are constricted in the rigor of their methodology as well. These articles, however, do provide important insights into the time period covered by the research, database searches, and criteria for adding or excluding literature. which provide significant information on the study's timeline, database search, and inclusion and exclusion standards for literature. Our evaluation summarizes the practical literature while also adding to the body of theoretical studies in the analytics literature. Present theoretical evaluations are limited to methodological challenges, Cartiolovni et al. [29] and Cheerkoot-Jalim and Khedo [13] their resolutions and the use and outcomes of big data analytics in healthcare [21]. In this review, we outline the components, techniques, range, or medical subarea, timing, and quantity of publications assessed. The following research questions are expected to be addressed by this systematic review with new perspectives:

- We present a cutting-edge comprehensive evaluation of existing HI challenges, solutions, and validation based on diverse AI approaches.
- We examine the major benefits and drawbacks of the many currently used strategies and discuss cutting-edge AI techniques as an emerging methodology in HI in order to pinpoint the most recent and novel viewpoints in this field of study.
- We address numerous remaining difficulties that contribute to this exciting new AI-based field.

Difference between this survey and former ones: This survey differs from previous ones in several ways. Firstly, it focuses on evaluating AI techniques in HI from several studies, which have not been explored in depth in previous studies, for example, where they used lasso regression, autoencoder, and ridge regression [33,34]. Furthermore, this survey contrasts with former ones that primarily focused on evaluating HI systems for AI, by evaluating the impact of user characteristics and different layouts and visualizing for better information of machine learning (ML) models, the state-of-the-art predictive HI, interactive ML, interpretable ML, and deep learning (DL) techniques [35,36]. Moreover, the current survey is largely concerned with (1) an interactive clinical-decision-support system [37]; (2) healthcare informatics prediction of chronic diseases [38–40]; (3) medical time-series data [41–43]; (4) health care recommendations [44]; (5) prediction task for records and a real-fake contrastive learning problem [45–47]; (6) the most recent HI apps [48–50]; surveys of multidimensional AI techniques [8,51]; and more survey as shown in Table 1. However, it is important to note that there is research that covers the relevant subject. Furthermore, rather than focusing on the overall implications of using such techniques, we emphasize how current evaluation procedures support tackling the challenges outlined above.

Objectives: This field of study has a number of difficulties, including dealing with using training datasets originating from irregular sources. Several studies are still working on enhancing their technological capabilities and are not yet at the point where they can make mature healthcare assessments. Individuals and experts in participatory HI may now achieve vital knowledge from a number of online sites thanks to AI. This article's goal is to provide an overview of the present state of the art and potential applications of AI in the field of HI. Some of the objectives of HI include the following:

- Using technology to increase the efficacy of healthcare delivery and the standard of patient care by giving healthcare workers accurate and timely information.
- Improving population health management through the use of digital medical records and patient engagement and self-management through the use of mobile health and telemedicine.

Table 1 | Existing health informatics publications and their objectives

References	Focus
Rajkomar et al. [52]	Disease diagnosis and prediction
Litjens et al. [53]	Medical image analysis
Tekkesin et al. [54]	Personalized medicine
Carracedo-Reboredo et al. [55]	Drug development and research
Bashshur et al. [56]	Telemedicine and remote patient monitoring
O'donoghue et al. [57]	Health behavior and lifestyle analysis
Roy et al. [58]	Natural language processing for HI
Topol et al. [59]	Robotics and automation in healthcare
Moingeon et al. [60]	Clinical decision support systems using AI
Kishor and Jeberson [61]	Prediction of heart disease

- Facilitating communication and collaboration among healthcare providers and patients.
- Fostering innovation in healthcare through the use of ML and data science methods.

Contributions: This study offers a state-of-the-art review of some of the most important applications in the area of HI, as well as an exploration of a number of issues and multiple research directions. It offers an in-depth analysis of "the most significant health approaches", "how they are applied in various applications of HI areas?", and "what are the challenges and prospects of HI research?". The main focus of this study is to assess the benefits and drawbacks of various evaluation techniques and offer solutions for the latter. Here is an overview of our paper's main contributions:

- We conducted a survey of state-of-the-art research through an explanation of AI applications in the HI sector.
- We discussed the most up-to-date and widely used techniques for HI and provided historical context by examining multiple applications that have been published in a number of well-known journals and conferences.
- We have discussed a few challenges and future directions to assist in gathering knowledge about AI applications for HI.

The remaining sections are arranged as follows: Section 2 gives a general summary of the implications of HI. Section 3 explains our database search approach for reviews and the criteria we used to choose the papers. Section 4 summarizes the many datasets utilized in cutting-edge research for AI for healthcare informatics. Section 5 explains current difficulties and potential future study areas. Finally, Section 6 concludes the paper.

2. BACKGROUND STUDY

This section, first, defines health informatics (HI) as the field concerned with the use of information technology to improve healthcare delivery, outcomes, and patient experience. We then discuss the role of artificial intelligence (AI) and machine learning (ML) techniques in HI, highlighting how these technologies can assist with tasks such as disease diagnosis, prognosis, and treatment planning. We also examine the emergence of deep learning (DL) techniques, which have shown potential for enhancing the precision and effectiveness of medical image analysis, natural language processing (NLP), and other health-care-related tasks. Finally, we discuss the potential impact of AI on HI, including the benefits and challenges of integrating these technologies into clinical practice.

2.1. Health Informatics

Health informatics (HI) is a multidisciplinary field that involves enabling healthcare's effective use of technological innovations in communication and information, computer science, information science, and health sciences must be combined. It plays a critical role in managing and processing vast amounts of health-related data, including electronic health record (EHRs), clinical data, telemedicine, health information exchange, mobile health applications, imaging data, and genomics data [62,63]. HI helps healthcare organizations access, store, and analyze health data to support patient care, population health management, and decision-making [64]. HI helps healthcare providers improve the accuracy, efficiency, and safety of patient care by leveraging modern technology such as AI, ML, and natural language processing (NLP). AI applications in HI include predictive analytics, personalized medicine, patient stratification, and clinical decision support systems [10].

Currently, HI using AI has been growing rapidly, leading to significant advancements in areas such as diagnosis, treatment planning, and drug development. However, there are still challenges to the widespread implementation of AI in healthcare, including data privacy and security, ethics, and regulatory barriers. Despite these challenges, the future of HI is poised to be shaped by AI and other advanced technologies that will continue to revolutionize the healthcare industry [5]. AI technologies, including ML and DL, have already demonstrated their potential in various areas of healthcare, such as medical image analysis, drug discovery, and disease diagnosis, among others [65].

In conclusion, HI is a crucial field that has the capacity to change healthcare delivery and enhance health results. With the advent of AI and other advanced technologies, the future of HI looks bright and holds tremendous potential for improving the lives of patients and healthcare providers.

2.2. Artificial Intelligence Technologies

Although AI for HI has been well-developed and is important in this field, there is still a need for ongoing development. Artificial intelligence technologies refer to computer systems that are created to carry out activities that normally require human intellect, like voice recognition, decision-making, or seeing patterns in data. These innovations allow machines to extract information from information and develop assumptions based on it using algorithms and mathematical models [66,67]. In recent years, AI technologies have made significant advancements, leading to their widespread use in a variety of industries, including healthcare. The interrelation between AI, ML, and DL is visually depicted in Figure 2, showcasing the interconnectedness and hierarchical nature of these domains. In HI, AI technologies are being used to support improved patient outcomes and increase the efficiency of delivery clinical decision-making in healthcare. AI applications in HI include predictive analytic, personalized

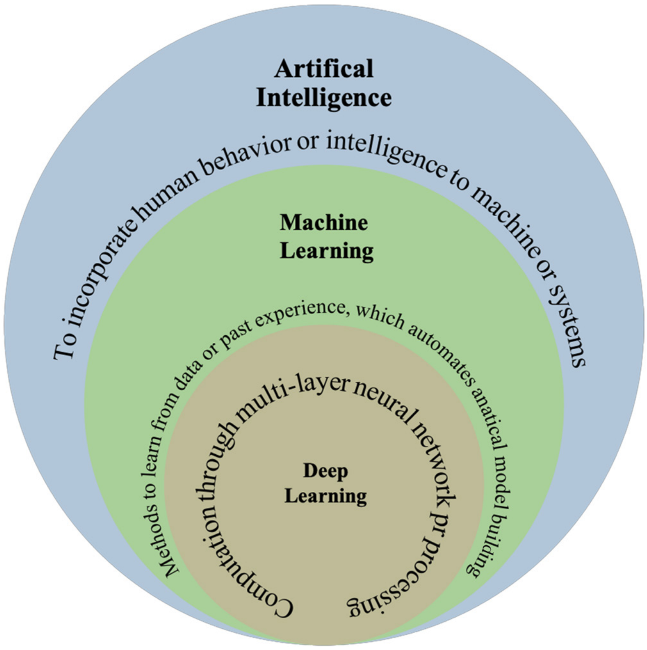

Figure 2 | AI fields illustrations.

medicine, patient stratification, and clinical decision support systems [5,68].

Machine learning involves the development of algorithms that enable machines to perform better on a certain task through experience. It is a key technology for HI, as it allows health systems to examine enormous volumes of clinical data, EHRs, imaging data, and other data in order to spot trends and forecast outcomes. ML algorithms have been used in a wide range of HI applications, including diagnosis and treatment recommendations, population health management, and predictive modeling of disease risk [69,70]. Similarly, DL is a subset of ML that employs multiple-layer artificial neural networks to perform complex computations. DL algorithms have been used for tasks such as image analysis, speech recognition, and NLP. In the context of HI, DL algorithms have been used for tasks such as detecting abnormalities in medical images and analyzing genomics.

The importance of AI technologies in HI lies in their ability to extract meaningful insights from vast amounts of data and to support decision-making in healthcare. As healthcare becomes increasingly data-driven, AI technologies are becoming an essential tool for healthcare organizations and researchers. By leveraging the power of AI, HI can support improved patient outcomes, better resource allocation, and more efficient healthcare delivery. Despite the many benefits of AI in HI, there are also challenges to its widespread adoption. These include data privacy and security, ethics, and regulatory barriers. There is also a need for robust validation and testing of AI systems to ensure that they are safe, effective, and accurate [5]. To conclude, HI and healthcare delivery might be greatly enhanced by AI technology. The future of HI is anticipated to be strongly influenced by AI technology due to its capacity to handle enormous volumes of data, help clinical decision-making, and improve patient outcomes.

2.2.1. Machine Learning Techniques

Machine learning is a powerful technology that uses algorithms to learn from data and make predictions. It has been used for years in biomedical research to discover patterns in data and improve decision-making. However, smaller research labs often don't use these strategies to their full potential. Health informatics focuses on using probabilistic information to make decisions in healthcare. Combining ML and HI has the potential to improve the quality, effectiveness, and efficiency of treatment and care.

There have been a number of applications of ML techniques applied to various aspects of patient care such as diagnosis, treatment planning, and disease prediction. ML is used to monitor patients in real-time by analyzing data from different sensors or devices. This is particularly useful in intensive care units [71]. Researchers have also focused on monitoring physical activity patterns from body-fixed sensor data for the past two decades [72]. This is important for understanding the link between physical activity levels and health problems like diabetes, cardiovascular diseases, and osteoporosis, especially as people become more sedentary.

A study by Li et al. [73] of ML techniques to EHRs to predict the risk of readmission for patients with heart failure and demonstrated the potential of these technologies to support clinical discretion with the enhanced patient results. Another example by Wang and Tao [74] developed an ML model for diabetic retinopathy disease and demonstrate the potential of technologies to support early diagnosis and prevent vision loss. Furthermore, there have been a number of other studies exploring the proper use of ML in HI, including the use of ML for disease classification, drug discovery, and personalized medicine [75].

In summary, ML technologies hold tremendous potential for improving HI and healthcare delivery. With their ability to learn from data, make predictions, and support clinical decision-making, the future of HI is expected to be significantly shaped by ML technology.

2.2.2. Deep Learning Techniques

Deep learning technologies are a subfield of ML that uses artificial neural networks for decision-making, voice and image recognition, and other activities that traditionally require human intellect. In recent years, DL has become increasingly important in HI, with a growing body of research demonstrating the potential of these technologies to improve health outcomes and healthcare delivery.

There have been a number of studies exploring the use of DL in HI, including the application of DL techniques to various aspects of patient care such as medical image analysis, diagnosis, and disease prediction. For example, a study of dermoscopic images to diagnose skin cancer demonstrates the potential of deep neural networks (CNN) to support early diagnosis and improve patient outcomes [76]. Another example is to develop a predictive model for diabetic retinopathy, a serious complication of diabetes that can cause vision loss. The study has shown that the DL model has the ability to accurately predict diabetic retinopathy, demonstrating the potential of these technologies to support early diagnosis and prevent vision loss [77]. In addition to these examples, there have been a number of other studies exploring the use of DL in HI, including the use of DL for drug discovery, personalized medicine, and disease classification [78]. Magnetic resonance imaging (MRI) scans to diagnose Alzheimer's disease. The study demonstrated the potential of DL technologies to support early diagnosis of Alzheimer's disease and improve patient outcomes [79]. Mammographic images to diagnose breast cancer. The study showed that the DL model was able to accurately diagnose breast cancer, demonstrating the potential of these technologies to support early diagnosis and improve patient outcomes [80]. These studies highlight the potential of DL technologies to revolutionize healthcare and improve health outcomes for patients.

In summary, DL is an important technology in HI, offering the potential to improve diagnosis and disease prediction, personalized medicine, and clinical decision-making. These benefits have led to a growing number of studies that have used DL techniques in the field of HI, highlighting the potential of these technologies to revolutionize healthcare and improve patient outcomes.

2.3. Impact of Artificial Intelligence on Health Informatics

The discipline of HI has increasingly embraced AI, with a significant impact on various aspects of healthcare, including diagnosis, treatment, and management of patients. The integration of AI in healthcare has led to improvements in accuracy, efficiency, and speed of decision-making, thereby contributing to better patient outcomes. The following is an overview of the impact of AI in HI and a discussion of some of its potential benefits.

- **Improved diagnosis and disease prediction:** By evaluating vast volumes of data and seeing trends that may not be immediately obvious to healthcare professionals, AI technologies, in particular ML and DL, offer the potential to help improve illness diagnosis and prediction [38,81]. This can help to improve patient outcomes by enabling earlier and more accurate diagnoses.
- **Better treatment planning:** AI can also be used to create individualized treatment strategies for each patient. For example, AI algorithms can analyze patient data, such as genetic information and medical history, to determine the best treatment options for a specific patient. By doing so, medical professionals may make better judgments and treat their patients more effectively [66].
- **Personalized medicine:** Using AI technology, it is possible to evaluate patient data and provide individualized treatment regimens, helping to ensure that patients receive the most effective and appropriate treatments for their individual needs [49].
- **Improved clinical decision-making:** AI technologies can support clinical decision-making by providing healthcare providers with real-time access to patient data and enabling them to quickly identify and respond to potential health issues [9].
- **Increased efficiency and cost savings:** AI technologies can help to increase efficiency and reduce costs by automating routine tasks and freeing up healthcare providers to focus on more complex and critical issues [5].
- **Predictive analytics:** AI can be used for predictive analytics in healthcare, allowing medical practitioners to identify and predict potential health problems and make proactive decisions. For example, AI algorithms can analyze patient data and predict the likelihood of a specific disease, allowing medical practitioners to intervene earlier and prevent the progression of the disease [82].
- **Improved resource management:** AI may also be used to enhance hospital strategic planning. For example, AI algorithms can analyze patient data and identify trends and patterns that can help medical practitioners better allocate resources, such as staffing and equipment, to improve efficiency and reduce waste [1].

In conclusion, AI technologies are having a significant impact on HI and are poised to play an increasingly important role in determining how healthcare is delivered in the future. By improving diagnosis and disease prediction, personalized medicine, clinical decision-making, and increasing efficiency and cost savings, AI technologies have the potential to revolutionize healthcare and improve health outcomes for patients.

3. REVIEW METHODOLOGY

In this section, we reviewed the published scientific research papers systematically using a standard systematic literature review (SLR) technique in accordance with the studies that have already been conducted. Also, the bottom-up collection of pertinent publications was done using the interdisciplinary approach [83]. Instead of particular journals, the papers were collected from important online databases. For the investigation, we used a four-phase SLR method:

- Phase-I: To find the first batch of relevant papers, we searched the top 6 online databases as shown in Figure 3. 582 relevant studies for the SLR were found. At the conclusion of this phase, duplicate articles were eliminated, leaving 553 items for screening.
- Phase-II: After finishing Phase-I, we thoroughly reviewed the articles' titles, abstracts, and keywords to weed out irrelevant articles from the preliminary research list. The list was then updated to remove prohibited items.
- Phase-III: After finalizing Phase-II, we read the full text from the articles which is assessed for eligibility for phase-III. This step ensures that only relevant and permissible articles are included in the final list for further analysis in Phase-IV.
- Phase-IV: To prepare the SLR, we ultimately chose 153 articles from 582 articles as shown in Table 2.

Recent developments in artificial intelligence (AI) and its application to HI are fairly and accurately described in the SLR. As a result, the SLR's findings may provide useful guidance for the development of AI technology and its use in health informatics (HI).

3.1. Research Questions

The fundamental goal of the Application of HI is to answer the four research questions (RQs) about AI listed below.

- RQ1: How does the implementation of AI technology in HI affect patient outcomes and healthcare providers' decision-making processes?
- RQ2: What are the moral implications and concerns connected with the employment of AI in HI, and how can they be addressed to ensure responsible and beneficial implementation in the healthcare industry?
- RQ3: What are the potential ethical and legal implications of using AI in HI, and how can they be addressed to ensure the safety and privacy of patients?
- RQ4: How can ML algorithms be used to increase illness detection and treatment accuracy and efficiency planning in HI?

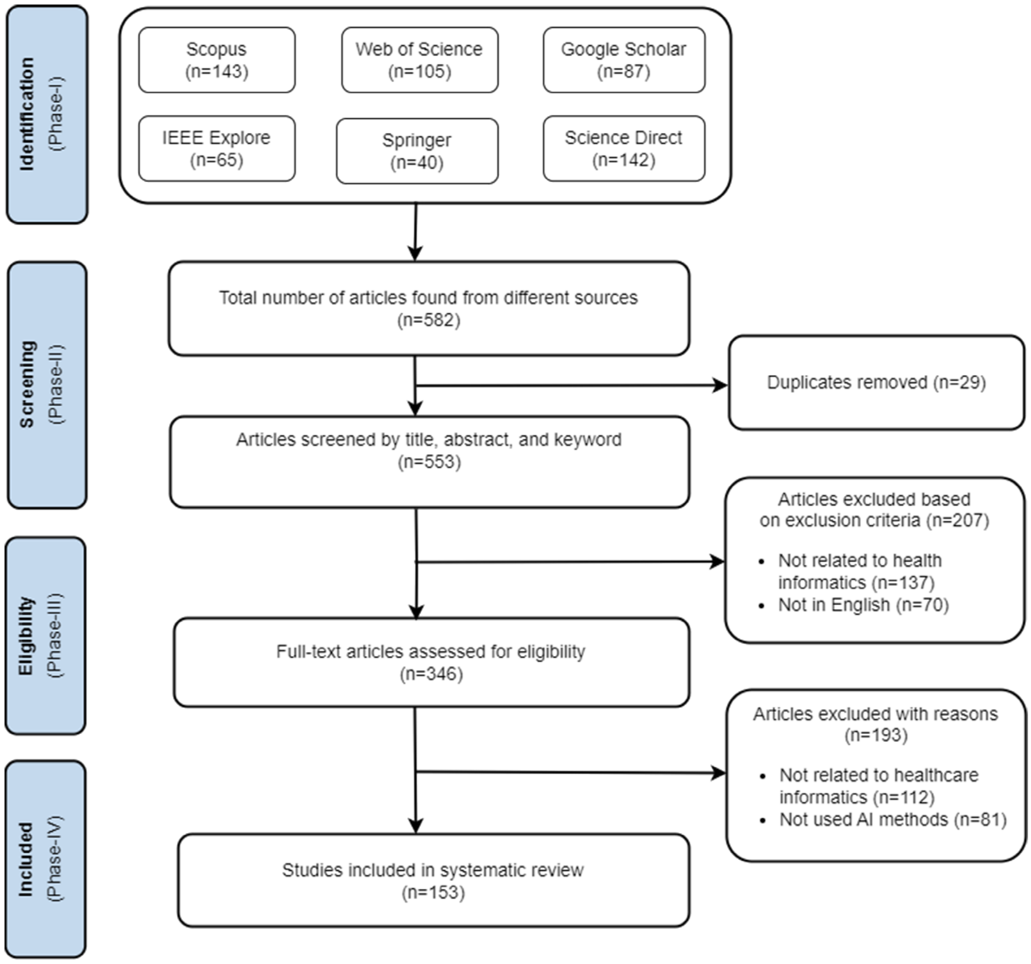

Figure 3 | PRISMA flowchart for systematic publication selection and evaluation.

Table 2 | **Search engines and the number of articles**

Search engine	Preliminary article selection	Final article selection
Scopus	143	57
Web of Science	105	25
Google Scholar	87	16
IEEE Explore	65	15
Springer	40	17
Science Direct	142	23
Total	582	153

Table 3 | **Searching keywords for inclusion and exclusion of research studies**

ID	Keywords
1	Healthcare analysis
2	AI in healthcare
3	Healthcare informatics
4	Healthcare decision support systems
5	Evidence-based healthcare

We include RQ1 to comprehensively understand the implementation of AI technology and how to make decision processes of HI. RQ2 described the moral implications and concerns linked with the application of AI in HI, and how they can be addressed to ensure responsible and beneficial implementation in the healthcare industry. RQ3 discussed the legal implications of using AI in HI also how they can be addressed to ensure the safety and privacy of patients. Finally, RQ4 addressed how to increase the accuracy and efficiency of illness diagnosis and treatment planning in HI.

3.2. Searching Keywords

Throughout our database searches for relevant articles, we concentrated on the literary subject and the best precise synonyms. As shown in Table 3, we found the literature's most immediately relevant works using the principal alternatives and the "OR" and "AND" operators.

3.3. Screening Data

In addition to the articles, the first search result contains conference papers, books, and book chapters; however, everything except the articles was later removed. As a result, the search was limited to "article titles", "abstracts", and "keywords" to eliminate books, conference proceedings, and articles from the pile. As a consequence of the initial refining, 582 papers were kept as articles, as shown in Table 2. After deleting duplicates, 153 publications were ultimately selected for metadata analysis.

3.4. Selection Criteria

Selection criteria are essential in ensuring the inclusion of relevant and high-quality studies for a systematic review. In this study, we defined five inclusion criteria to identify the most suitable articles that meet our research objectives. First, the selected articles must focus on HI. Second, the focus of the research should be evident in the article's title, abstract, or keywords. Third, the selected articles must either employ traditional machine learning (ML) and/or deep learning (DL) models, which are subsets of AI, to classify HI or present a dataset related to HI. Fourth, if the article employs classification models, it must present a performance evaluation of the adopted models. Finally, the article must be written in the English language. These inclusion criteria were carefully chosen to ensure that only relevant and high-quality articles are included in this systematic review.

Preferred reporting items for systematic reviews and meta-analyses (PRISMA) was used to systematically select articles for this study, as illustrated in Figure 3. Initially, 582 papers were identified through database searches during the 'identification' phase. After removing 29 duplicate articles, 553 articles were screened in the 'screening' phase using the inclusion criteria and keywords in the titles and abstracts. Based on this, 207 articles were excluded, leaving 346 articles for the 'eligibility' phase, where the full texts were reviewed for final selection. Of the 346 articles, 193 were excluded because they did not relate to HI or do not employ any AI techniques. Finally, in the 'included' phase, we analyzed the remaining 153 papers that met our selection criteria.

3.5. Inclusion of Data

The inclusion of relevant and high-quality studies is crucial for the success of a systematic review. In this study, we used a comprehensive search strategy to identify potential studies that meet our selection criteria. We searched six electronic databases, namely scopus, web of science, google scholar, IEEE explore, springer, and science direct, to identify relevant studies published between 2015 to 2022. The search was restricted to papers published in English. In addition to the electronic database search, we also conducted a manual search of the reference lists of the included studies to identify additional relevant studies that may have been missed in the initial search. To ensure that our review encompasses the most up-to-date research on the topic. This time frame was chosen because it covers the period when the use of AI in HI gained popularity and became more widely studied.

The selected studies were then extracted and compiled into a database. The database included information about the study characteristics, such as the title, authors, publication year, study design, and sample size. For each study, we also extracted relevant data, including the type of AI algorithm used, the dataset(s) employed, the outcome(s) measured, and the performance of the AI algorithm. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines to ensure the transparency and rigor of our review process. The PRISMA flowchart was used to summarize the study selection process and document the number of studies included and excluded at each stage of the selection process [84].

The inclusion of relevant and high-quality studies is critical for a systematic review. We used a comprehensive search strategy and followed the PRISMA guidelines to ensure the inclusion of the most relevant studies for this study. The extracted data from the included studies will enable us to analyze the current state-of-the-art in AI for HI and identify new perspectives for future research.

3.6. Meta Data Analysis

This section presents a descriptive statistics analysis based on the metadata of 153 publications. The study takes into account a variety of factors, such as authors, countries, publication years, journals, subject areas, citations, and institutions. It should be noted that in cases where a paper has multiple authors, each author, and their affiliated institution are given credit for the publication. However, to increase readability, the statistics are presented in a summarized format instead of a full list in some instances.

3.6.1. Publications by year

A thorough study of the literature on AI's uses in HI was done by us, searching multiple electronic databases for articles published between 2015 and 2022. Figure 4 shows the volume of

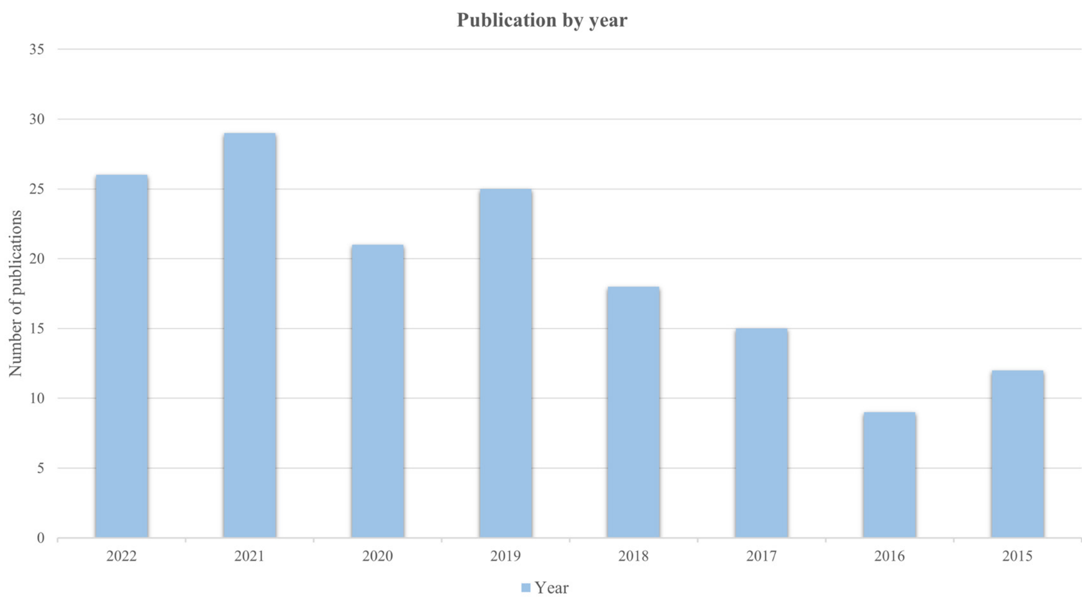

Figure 4 | Publications on year.

papers that were released annually throughout the research period. The publication of HI was established in 2015, with a steady increase continuing through 2022. There is a noticeable exponential surge in the number of publications beginning in 2015, with the trend line exhibiting a rising pattern, implying that the literature on HI is still developing. In the year 2021, 29 papers were published, which is a much higher number of publications than in prior years. This trend in the number of publications suggests increasing concerns and interest in the HI topic. The growth of research in this area also highlights the potential of AI to significantly impact and transform the field of HI in the future.

3.6.2. Publications by journals

To identify the top journals publishing research on the applications of AI for HI, we analyzed the 153 articles selected for full-text analysis in our systematic review. We found that these articles were published in 70 different journals, indicating a wide distribution of research on this topic. Figure 5 presents the top 10 journals publishing research on the applications of AI for HI. The Journal of Studies in Health Technology and Informatics published the most papers (20), accounting for almost 13% of the total 153 papers. The International Journal of Evidence-Based Healthcare is the second most popular journal, publishing around 11% of total publications on HI, ranking the journal among the best in this area. However, there is still room for growth in terms of the number of journals publishing research on this topic, which is expected given the rapid pace of development in this field.

3.6.3. Publications by authors

Figure 6 displays the top ten authors with the most publications on HI, according to our search results in the ISI web of science and scopus databases. Munn, Z. published the most

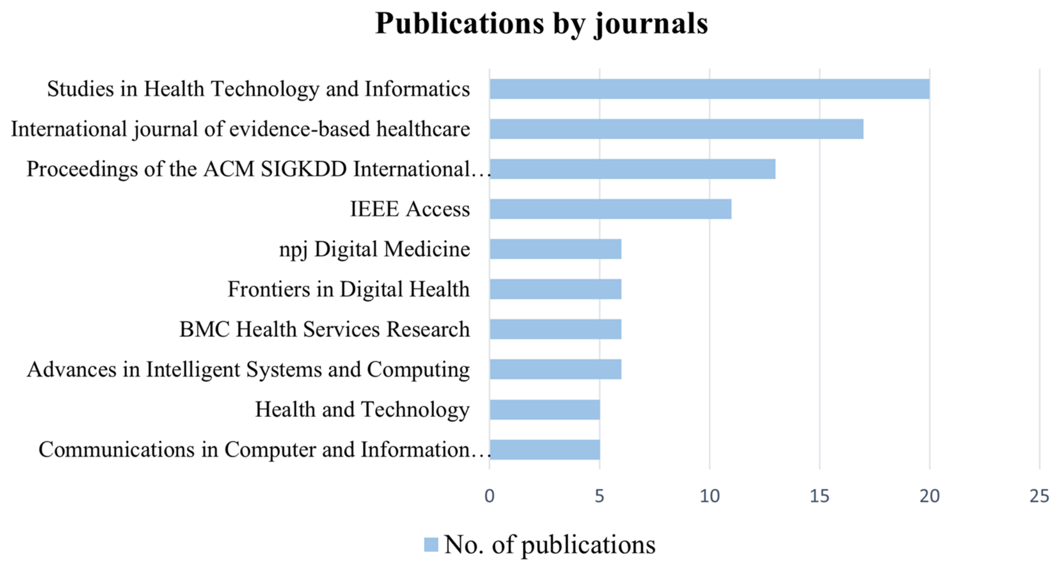

Figure 5 | Publications on journals.

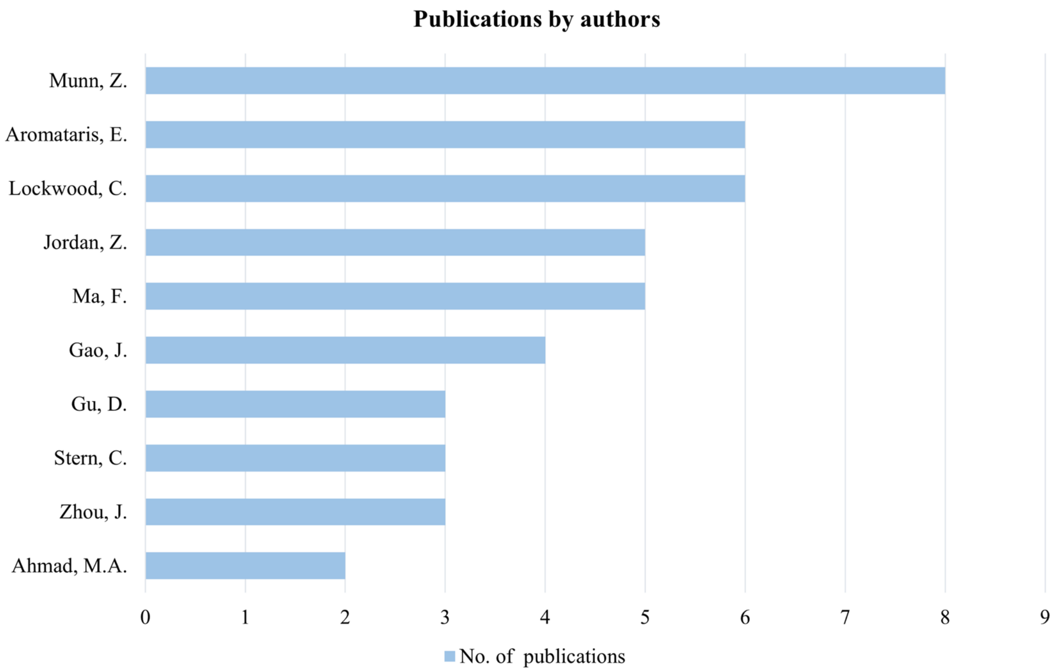

Figure 6 | Publications on authors.

publications on HI (8 out of 153), accounting for around 5% of the total. Lockwood, C., and Aromataris, E., are the second and third most-published writers, respectively. These authors have all made significant contributions to the field of HI, and their work has been widely cited and acknowledged by other researchers in the field. We also compared the number of papers published by each author across the scopus, web of science, google scholar, IEEE explore, springer, and science direct databases. This comparison allowed us to gain a better understanding of the top authors in the field as well as any discrepancies in their publication records across different databases. Our analysis revealed that there were some discrepancies in the number of publications listed for certain authors, but overall, the top authors were consistent across both databases.

3.6.4. Publications by citations

To identify the most highly cited papers, the study examined the scopus database as of December 2022, noting that citation counts may differ across other databases such as web of science, google scholar, IEEE explore, springer, and science direct. Table 4 shows the top ten most cited papers, based on scopus data, with the paper by Munn et al. [85] published in 2018, receiving the highest number of citations (2578). Overall, the authors of these highly cited papers can be considered among the leading contributors to the HI literature. It is crucial to note, however, that citation numbers alone may not always represent a paper's quality or effect, since other factors such as the context in which it was mentioned, or the influence of the citing author can also play a role.

3.6.5. Publications by countries

Figure 7 shows that the United States is the leading country in HI research, with 52 published papers, accounting for around 34% of the total publications. Australia is the second-highest contributor with 19 papers, followed by China with 17 papers. The top ten countries by the number of publications also include

Table 4 | **Top ten cited publications**

Authors	Title	Year	Citations
Munn et al. [85]	Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach	2018	2578
Lockwood et al. [86]	Qualitative research synthesis: methodological guidance for systematic reviewers utilizing meta-aggregation	2015	532
Ma et al. [87]	Dipole: diagnosis prediction in healthcare via attention-based bidirectional recurrent neural networks	2017	303
Munn et al. [15]	What kind of systematic review should I conduct? A proposed typology and guidance for systematic reviewers in the medical and health sciences	2018	259
Kraemer et al. [31]	Fog computing in healthcare – a review and discussion	2017	204
Bardou et al. [88]	Classification of breast cancer based on histology images using convolutional neural networks	2018	201
Patel et al. [64]	Federated learning for healthcare informatics	2021	168
Baig et al. [39]	A systematic review of wearable patient monitoring systems – current challenges and opportunities for clinical adoption	2017	163
Moola et al. [89]	Conducting systematic reviews of association (etiology): The Joanna Briggs Institute's approach	2015	162
Amann et al. [68]	Explainability for AI in healthcare: a multidisciplinary perspective	2020	153

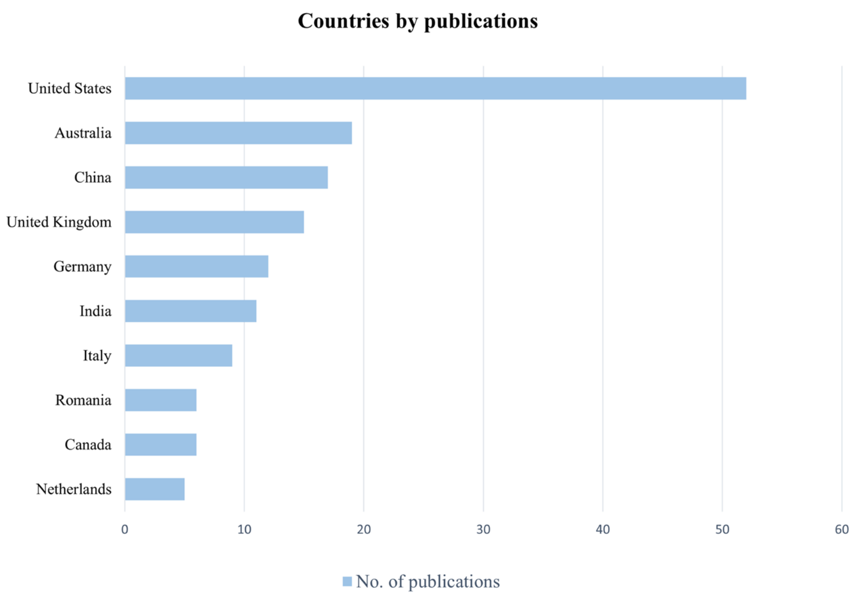

Figure 7 | Publications on countries.

China, United Kingdom, Germany, Italy, Romania, Canada, and the Netherlands. It is important to note that the distribution of HI publications may be influenced by several factors such as research funding, academic institutions, and government policies. Moreover, regional factors, such as disease burden, technological advancement, and healthcare infrastructure can also influence publication patterns in HI. This suggests that these countries have recognized the importance of HI and have invested resources in research and development.

3.6.6. Most common words used in the title

In order to gain a better understanding of the most common themes and keywords used in HI publications, this study conducted a search using the free, open-source online software wordart.com. The results of this analysis, presented in Table 5, show that the most commonly used word in the titles of these publications is "health informatics," which appears in 383 titles. This type of analysis is a useful and efficient approach to identifying common themes and keywords in a complex research field and can provide valuable insights for researchers in this area.

3.6.7. Publications by institutions

Figure 8 showed that the University of Adelaide was found to be the leading contributor to the field with 10 published papers. This represents approximately 3.6% of the total papers published, indicating their significant contribution to the advancement of HI research. It is worth noting that there were several other institutions that also made valuable contributions to the literature, and further research could be done to explore their impact on the field. Overall, the findings demonstrate the diverse range of institutions involved in HI research, and the collaborative effort needed to push the field forward.

Table 5 The title's most prevalent words

Words	Numbers	Words	Numbers
Healthcare	383	Model	178
Analysis	261	Health	171
Data	242	Medical	169
AI	236	Patient	160
Base	197	Study	139

3.6.8. Publications by subject area

One of the most remarkable aspects of the HI field is the variety of disciplines that contribute to it. From medicine to computer science, from engineering to public health, HI research is interdisciplinary and multidisciplinary. To gain a better understanding of the range of disciplines involved in the field, the study analyzed the contributions made by different subject areas.

As shown in Figure 9, the majority of the papers included in the study were contributed by the medicine, computer science, and engineering disciplines, accounting for 31% of the total HI literature. This indicates that there is a strong intersection between HI and the technical fields. Computer science was the second-highest area, with 15% of the literature, which shows the growing importance of technology in healthcare. The interdisciplinary nature of HI research not only makes it more complex but also offers a broader scope to explore and solve the issues faced by the healthcare industry.

3.6.9. Publications by type

The distribution of publications by type in the HI literature found that 58% of the publications are articles, which is the most common type of publication. The conference papers account for 27% of the publications, while reviews make up 15% of the publications. This indicates that articles are the most preferred type of publication in the field of HI, followed by conference papers and reviews.

4. ARTIFICIAL INTELLIGENCE FOR HEALTH INFORMATICS: STATE-OF-THE-ART

In this section, we present a comprehensive overview of the current state-of-the-art in Artificial intelligence (AI) for health

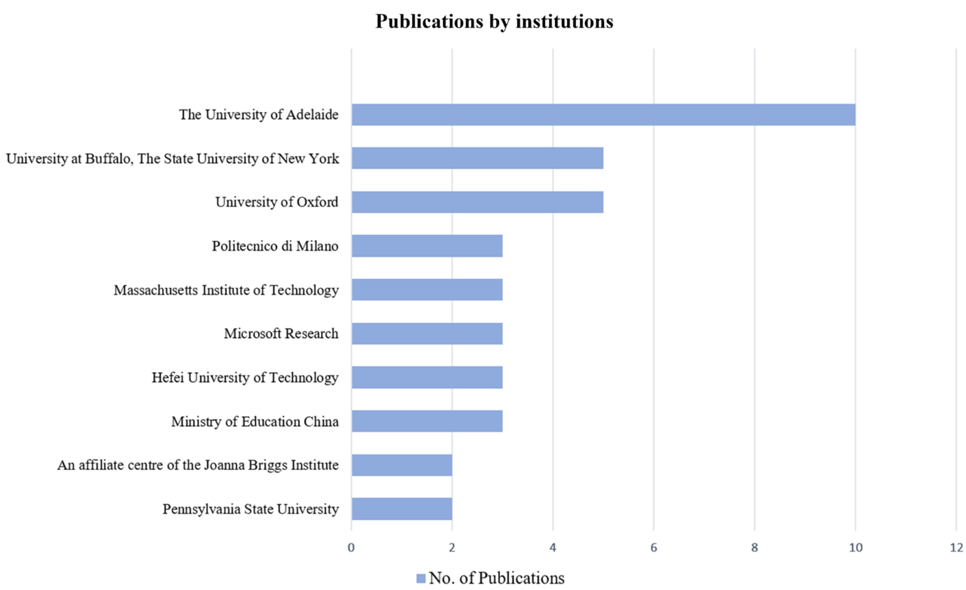

Figure 8 Publications by institutions.

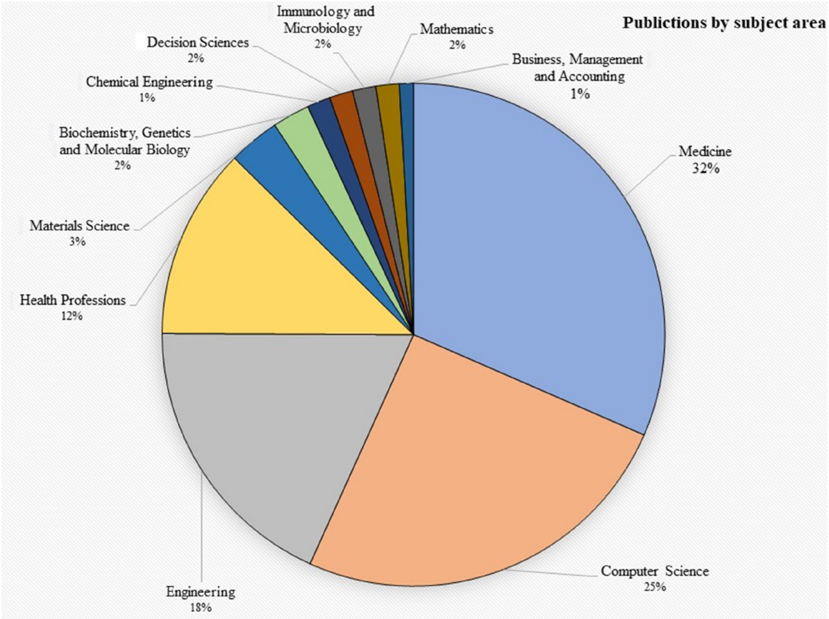

Figure 9 | Contribution by subject area.

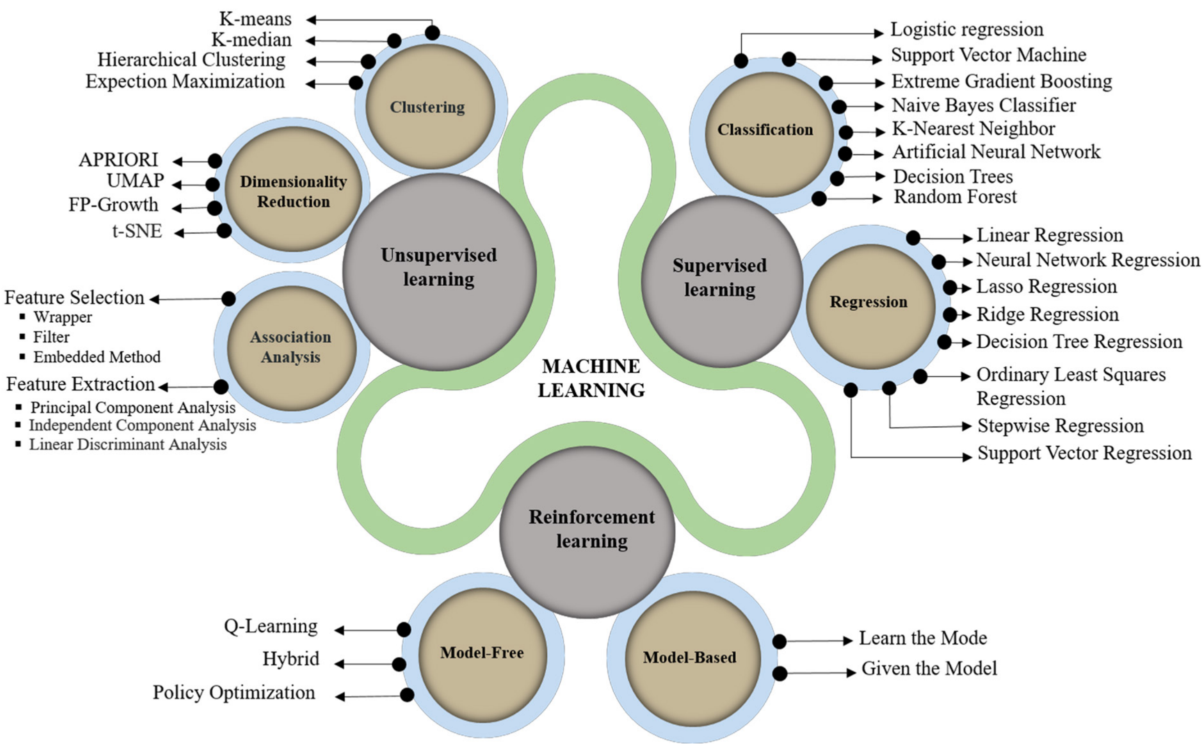

Figure 10 | ML techniques can be categorized into three main groups: (i) supervised learning, (ii) unsupervised learning, and (iii) reinforcement learning.

informatics (HI). Various AI algorithms and techniques are used in HI, including machine learning (ML), deep learning (DL). ML programs learn from data and produce predictions, whereas DL algorithms examine massive volumes of data to find patterns and correlations. NLP is used to analyze unstructured data such as medical notes, free text, and reports [90].

A collection of technologies known as AI enables robots and computers to mimic human intellect. AI has garnered a lot of attention from a range of areas due to its potential to automate many jobs that presently need human participation. Nowadays, computer vision, voice recognition, and NLP all benefit from the use of AI approaches. Recent rapid improvements in computer hardware and software have facilitated the digitization of health data, opening up new paths for the building of computational models and the ability to apply AI systems to draw insights from data in the field of HI [67].

4.1. Machine Learning for Health Informatics

Machine learning is a powerful tool for analyzing large amounts of data in HI. ML algorithms may understand patterns and correlations in data, enabling the creation of prediction models and clinical decision support systems. Our research explored the use of ML in HI, as shown in Figure 10, and highlighted its potential applications in areas such as clinical decision support, disease prediction and diagnosis, patient risk stratification, personalized treatment planning, and other relevant data to predict the risk of various health outcomes, such as hospital readmissions and disease progression [95]. One of the key benefits of ML in healthcare is its ability to provide personalized treatment plans for individual patients. ML algorithms can analyze patient data and develop predictive models that take into account the patient's unique characteristics and medical history [6,39]. ML algorithms can analyze patient data and develop models that take into account the patient's medical history, genetic information, and other relevant factors to provide personalized treatment recommendations [66].

One of the challenges of using ML in healthcare is the need for high-quality, diverse, and representative data. It is important to have effective data management and governance practices in place to ensure that data is collected and stored in a manner that is ethical, secure, and in compliance with relevant regulations. ML is a powerful tool that has great potential for transforming healthcare by enabling personalized treatment plans and improving clinical decision-making [50]. As the area of ML in healthcare evolves, it will be critical to solving the problems related to data quality and privacy in order to achieve the full potential of this technology. Throughout our research, we have discovered various techniques as well as the outcomes of their proposed method. As shown in Table 6, we've reviewed the techniques used in those papers. In Table 7, we've analyze the outcomes of applying these techniques. This thorough inquiry gives useful insights into the effectiveness and performance of these various approaches, laying the groundwork for our study and understanding of this field. These ML techniques are thoroughly reviewed here in the next.

4.1.1. Linear Regression (LR)

LR is a widely used statistical technique that has several applications in HI. One of the key applications of linear regression in healthcare is predictive modeling [92], where it can be used to develop models for predicting patient outcomes based on clinical and demographic variables. Linear regression can also be used for analyzing the relationship between different variables, such as the relationship between a patient's age and their likelihood of developing a particular condition. Also, Combi et al. [105] used LR to identify factors associated with an increased risk of hospital readmissions, finding that factors such as age, gender, and comorbidities were significant predictors. While linear regression has its limitations, such as the assumption of linearity between variables and the need for a large sample size, it remains a valuable tool for predictive modeling and analyzing the relationship between variables in HI.

4.1.2. Random Forest (RF)

RF is an ensemble ML algorithm that is used in HI due to its ability to handle high-dimensional and complex data sets. It is particularly useful in HI because of the need to analyze large amounts of data, extract important features, and make accurate predictions [101]. This algorithm works by creating multiple decision trees and aggregating their predictions to obtain a final output. It has been applied in various healthcare applications, such as diagnosis, prognosis, and prediction of diseases. One study by Butt et al. [35], applied the RF algorithm for the prediction of COVID-19 severity using clinical and demographic data of patients. The study showed that RF outperformed other ML algorithms such as LR and SVM, and identified important features for predicting the severity of COVID-19. This algorithm has some limitations such as the potential for overfitting, difficulty in interpreting the results, and computational complexity. Overall, the RF algorithm has proven to be an important tool for HI due to its ability to handle complex and high-dimensional data sets and its potential for accurate predictions in various healthcare applications. Further research is needed to address its limitations and explore its full potential in healthcare.

4.1.3. Naive-Bayes (NB)

NB is a probabilistic ML algorithm that has shown promising results in various applications of HI. NB is popular in medical diagnosis and disease prediction due to its ability to handle large datasets with high dimensionality, especially in cases where data is sparse. It can also be used to identify risk factors for certain diseases and to classify patients based on their medical histories. For instance, Hasan and Bao [82] employed NB for heart disease classification, achieving an accuracy of 88.46%. Additionally, Rama Sree et al. [38] used NB to classify thyroid disease, obtaining an accuracy of 95.13%. Its strength lies in its ability to handle noisy and incomplete data, making it particularly useful for medical data analysis. However, the limitation of its assumption of independence among variables may not always be valid in real-world applications. NB remains an important tool in HI due to its ease of implementation and accuracy in various medical applications.

4.1.4. Decision Tree (DT)

DT is an important ML algorithm for HI due to its ability to generate intuitive decision rules based on complex medical datasets. This technique has been widely used in various healthcare applications, including clinical decision-making, disease diagnosis, and patient monitoring. A study by Rama Sree et al. [38], was used to develop a prediction model for postoperative complications in patients undergoing colorectal surgery. The authors reported that the DT model achieved 75.3% accuracy and outperformed other ML algorithms such as LR and RF. While it has several advantages, such as interpretability and ease of use, it also has some limitations, such as its tendency to overfit the training data and its inability to handle continuous variables. DT's contributions to HI research are significant, and its innovations in model optimization and pruning have increased its effectiveness in solving real-world healthcare problems.

4.1.5. Support Vector Machine (SVM)

SVM is an essential ML technique for HI owing to its capacity to handle large datasets with high-dimensional characteristics. This technique has been utilized for different applications in HI, including medical diagnosis, picture classification, and gene expression analysis. For instance, Hasan and Bao [82] used to predict the severity of COVID-19 based on chest X-ray images; Faris et al. [97] used SVM to classify ECG signals for the diagnosis of atrial fibrillation; and, Rama Sree [38] used predicting the risk of developing type 2 diabetes. SVM's strength in handling non-linear data has been beneficial in these studies, allowing for accurate classification and prediction. Additionally,

Table 6 Overview of various evaluation machine learning techniques and their applications

Year	References	Linear Regression	Random Forest	Naive Bayes Classifier	Decision Tree	Support Vector Machine	Extreme Gradient Boost	Logistics Regression	K-nearest Neighbours	Artificial Neural Network	Genetic Algorithm	K-means Clustering	Principal Component Analysis	Hybrid	Hierarchical Clustering	Publication venue
2022	Wang and Zheng [91]							✓								Frontiers in Public Health
	Ye et al. [92]	✓														J. Med. Internet Res.
	Tong et al. [93]														✓	J. Med. Internet Res.
2021	Priya et al. [94]						✓				✓					Health Technol.
	Rama Sree et al. [38]			✓	✓	✓		✓								AIST
	Tougui et al. [95]											✓		✓		Healthc. Inform. Res.
	Butt et al. [35]	✓	✓													J. Healthc. Eng.
	Lugner et al. [96]														✓	Diabetologia
	Hasan and Bao [82]			✓		✓			✓							Health Technol.
2020	Faris et al. [97]					✓										Biomed. Inform.
	Anjana et al. [98]											✓				BMJ Open Diabetes Res. Care
	Wang et al. [99]														✓	J. Biomed. Inform.
	Simsek et al. [100]									✓						DSS
	Sun et al. [101]		✓													IEEE JBHI
	Pradhan et al. [102]									✓						Elsevier
2019	Zubair Hasan et al. [103]										✓					Springer
	Long et al. [104]												✓			BioMed. Res. Int.
2018	Combi et al. [105]	✓														J. Biomed. Inform.
	Chen et al. [106]									✓						DSP
2017	Goodwin et al. [107]					✓										J. Biomed. Inform.
	Seleznev and Leonenko [108]												✓			ICDTGS
	Fomin et al. [109]									✓	✓					BICA-ERCE
	Gargeya and Leng [110]														✓	Ophthalmology
2016	Wimmer et al. [9]							✓								DSS
	Aljumah and Siddiqui [111]					✓										IAJIT

Table 7 Results of proposed machine learning algorithms

References	Purpose	Proposed methods results	Compared methods
Sun et al. [101]	Classification of COVID-19 using chest computed tomography images.	RF-Accuracy: 91.80%, Sen: 93%, Spe: 89.94%, AUC: 96.36%, Pre: 93%, F1-score: 93.06%	SVM, LR, NN
Hasan and Bao [82]	Feature selection for cardiovascular disease prediction.	NB-ACC: 80.8%, AUC: 84.6%	KNN, SVM, XGB
Rama Sree et al. [38]	Disease prediction in fundus retinography.	DT-ACC: 75.3%, AUC: 73.1%, Pre: 68.7%, Rec: 74.8%, Spe: 61.6%	LR, KNN, RF, SVM, NN
Faris et al. [97]	Medical speciality classification in fundus retinography.	SVM-ACC: 84.4%, Rec: 84.4%, Pre: 84.5%	XGBoost, KNN
Exley et al. [112]	Predict UPDRS motor symptoms in individuals with Parkinson's disease.	XGBoost-ACC: 74.1%, AUC: 87.8%, Spe: 83.3%, Sen: 87.5%	RF, SVM
Long et al. [104]	Detection of hardexudates in diabetic retinopathy.	PCA-ACC: 97.7%, Sen: 97.5%, Spe: 97.8%	SVM, RF
Basavaraju and Genesarathinam [113]	Automated detection of diabetic retinopathy.	K-means-ACC: 99.38%, Sen: 97.39%, Spe: 96.30%	DT, SVM, NV, RF
Chen et al. [139]	Classification of diabetic retinopathy.	ANN-ACC: 94.5%, Sen: 96.75%, Spe: 92.25%	SVM, KNN, DT
Gargeya and Leng [110]	To identify diabetic retinopathy.	HC-AUC: 97%, Sen: 94%, Spe: 98%	SVM, CNN

Goodwin et al. [107] and Aljumah and Siddiqui [111] identified these limitations and proposed solutions to improve SVM's performance, such as using an appropriate kernel function and optimizing hyperparameters. Overall, its ability to handle complex data and high-dimensional features has made it an important ML algorithm for various applications in HI.

4.1.6. Extreme Gradient Boosting (XGB)

In order to produce a more precise and reliable model for classification and regression problems in HI, the XGB ensemble learning approach combines a number of weak models. Decision trees are successively added to the model as part of the XGB process, each tree being created to rectify the flaws of the one before it. This method has been used in a variety of healthcare applications, such as predicting the risk of hospital readmission and identifying patients at risk of developing certain diseases [94]. It has several advantages, such as its ability to handle both categorical and continuous data, and its ability to identify important features for prediction. It can also handle missing data and is relatively easy to implement. However, XGB models can be computationally intensive and can be sensitive to the choice of hyperparameters used for training.

4.1.7. Logistics Regression (LogR)

LogR, a key tool in HI, utilizes patient data to classify and predict disease problems. This method has been used in a number of medical fields, including cancer, diabetes, and mental health. For instance, Wang and Zheng [91] achieved a 75% accuracy rate when using it to predict the probability of readmission in patients with mental illness. It was used by Rama Sree et al. [38] to categorize and predict cardiovascular disease among diabetic patients with an accuracy of 93.33%. This approach was used by Wimmer et al. [9] to predict the survival of patients with pancreatic cancer, with an accuracy of 86%. It cannot handle non-linear connections and makes the assumption that the independent and dependent variables have a linear relationship. These are some of its shortcomings. Despite this, LogR's contributions to and advancements in the area of HI make it a helpful tool for medical decision-making and personalized patient care.

4.1.8. K-nearest Neighbors (KNN)

KNN is a type of supervised learning algorithm used in HI for classification and regression issues. KNN initially calculates the K closest data points to a particular data point in order to categorize or forecast the value of a new data point based on the majority class or average value of its K nearest neighbors [82]. Several healthcare applications, including illness diagnosis and patient outcome prediction, have made use of KNN. This technique has a number of benefits, including simplicity, the convenience of use, and the capacity to handle both categorical and continuous data. It may also be used for binary and multi-class classification problems and performs well with limited datasets. With big datasets, KNN may be computationally expensive due to its sensitivity to the choice of K and the distance metric used to calculate the distances between the data points.

4.1.9. Artificial Neural Network (ANN)

The aptitude of ANNs to learn and model complicated correlations in data has led to their widespread use in the field of HI. The successful extraction of characteristics and classification of data by ANN makes it possible to help with illness diagnosis, prognosis, and therapy [102]. For instance, Simsek et al. [100] employed ANN to stratify and predict the risk of prostate cancer using blood PSA levels, age, and biopsy results in one of their studies. ANN was used in different research by Fomin et al. [109] to forecast the risk of postoperative complications in patients with colorectal cancer. Nonetheless, despite ANN's effectiveness, it has certain drawbacks, including the need for a substantial quantity of training data, high computing demands, and challenges in understanding the model's output. Despite this, ANN has significantly advanced the area of HI and continues to provide ground-breaking remedies for challenging medical issues.

4.1.10. Genetic Algorithm (GA)

The importance of GA as optimization algorithms for HI may be attributed to their capacity to identify the ideal set of attributes for use in predicting outcomes in health-related applications. Many HI applications, including drug discovery, customized medicine, and medical diagnostics, have made use of GA. As an example, Zubair Hasan et al. [103] used GA to forecast the likelihood of acquiring lung cancer based on information gleaned from medical imaging. In a different research, Fomain et al. [109] employed GA to pinpoint the key genes that contribute to the emergence of certain disorders, such as cancer. While GA has shown promising results in HI, its usage is constrained by a number of factors, including its sensitivity to startup and parameter choices. Nonetheless, it is a useful tool in HI applications due to its capacity to manage large-scale data and select the ideal combination of attributes.

4.1.11. K-means

Since it can find hidden patterns and groups within huge datasets, the unsupervised clustering algorithm K-means is a popular choice in HI. Disease diagnosis and patient classification are key K-means applications in the field of HI. For example, Tougui et al. [95] employed K-means clustering to separate asthmatic patients into subgroups based on their clinical and physiological characteristics. The methodology was effective in identifying four unique subgroups with various clinical traits and degrees of severity, which may guide individualized treatment plans. K-means clustering was used in different research by Anjana et al. [98] to categorize patients with diabetes into subgroups according to their metabolic features. The algorithm discovered three unique subgroups with various metabolic profiles, which may help with illness management and tailored therapy. While K-means has shown encouraging results in the field of HI, it has numerous drawbacks, including its sensitivity to initial cluster centers and its assumption of spherical clusters. Future studies may concentrate on overcoming these restrictions and investigating K-means' potential in diverse HI applications.

4.1.12. Principal Component Analysis (PCA)

Due to its capability to decrease the dimensionality of large datasets while keeping the most crucial characteristics, PCA is a crucial ML method used in HI. Applications of PCA in HI include feature extraction, image processing, and medical diagnosis. For example, Seleznev and Leonenko [108] for instance, demonstrated that the algorithm could reliably diagnose individuals with various forms of epilepsy by using PCA to extract characteristics from the EEG data of epileptic patients. Moreover, this technique has been used to predict clinical outcomes for patients with heart disease and to increase the precision of a cancer diagnosis made from medical pictures. It has significant drawbacks, including the potential for losing crucial information during the feature reduction process and the challenge of comprehending the resultant main components, despite its use. However, by enhancing the effectiveness and precision of ML algorithms used on huge healthcare datasets, PCA has significantly advanced the area of HI.

4.1.13. Hierarchical Clustering (HC)

For finding connections and assembling related items in data, HC is a crucial tool in HI. For instance, Wang et al. [99] identified subgroups with various prognoses by using unsupervised HC to group cancer patients based on their gene expression patterns. Similarly, Lugner et al. [96] compared HC with alternative clustering algorithms for identifying patient subgroups based on their comorbidities, confirming its value in producing clinically meaningful patient groups. This method has made significant contributions to HI, despite certain drawbacks such as its susceptibility to noise and outliers. Researchers may be able to find significant patterns and links in data by using its capacity to group related entities depending on their characteristics [93]. This might result in possible advancements in customized medicine, diagnosis, and treatment.

4.1.14. Reinforcement Learning (RL)

RL is a crucial ML technique for HI since it may be used to model and improve difficult healthcare decision-making processes. Recent research has shown that RL has considerable promise for improving patient outcomes and delivering individualized care in the medical field. In fact, a survey by Nie et al. [114] has demonstrated the potential of reinforcement learning on graphs, which has applications in diverse fields, including social networks, transportation systems, and bioinformatics. Moreover, the survey discusses the challenges of applying RL on graphs, such as scalability, generalization, and interpretability. Despite these challenges, RL on graphs offers significant opportunities for developing new healthcare solutions that can improve patient outcomes and enhance the quality of care. Furthermore, Tougui et al. [95] have successfully used RL techniques to improve the management of chronic illnesses, demonstrating the practical applications of this technique in the medical field. Other research has also used RL to improve cancer treatment regimens, forecast ICU patient death rates, and suggest therapies for patients with mental health issues. Nevertheless, RL still faces challenges such as data requirements, computer power, bias, and interpretability issues.

4.2. Deep Learning for Health Informatics

DL is a subset of ML that is particularly effective for analyzing complex data, such as medical images and signals. DL algorithms use multiple layers of artificial neural networks to learn patterns and relationships from data. As shown in Figure 11, DL techniques can be broadly categorized into different groups, with each group having its own unique characteristics and applications. DL algorithms have shown great promise in medical image analysis, with applications in the diagnosis and treatment of various diseases [65]. DL algorithms may be used for breast cancer early detection by analyzing mammogram images [88]. These algorithms can learn to identify subtle patterns in the images that are indicative of breast cancer, which can assist radiologists in making more accurate and timely diagnoses. Similarly, DL algorithms can be used to analyze MRI and CT scans to detect brain tumors and other abnormalities. Another application of DL in HI is in the analysis of EEG data. DL algorithms can learn to identify patterns in EEG signals that are associated with various neurological disorders, such as epilepsy and alzheimer's disease. This can assist in the diagnosis and treatment of these disorders, as well as in the development of new treatments.

One of the issues with employing DL in HI is the requirement for vast volumes of annotated data to adequately train the algorithms. This data needs to be diverse, high-quality, and representative of the population being studied. Additionally, DL

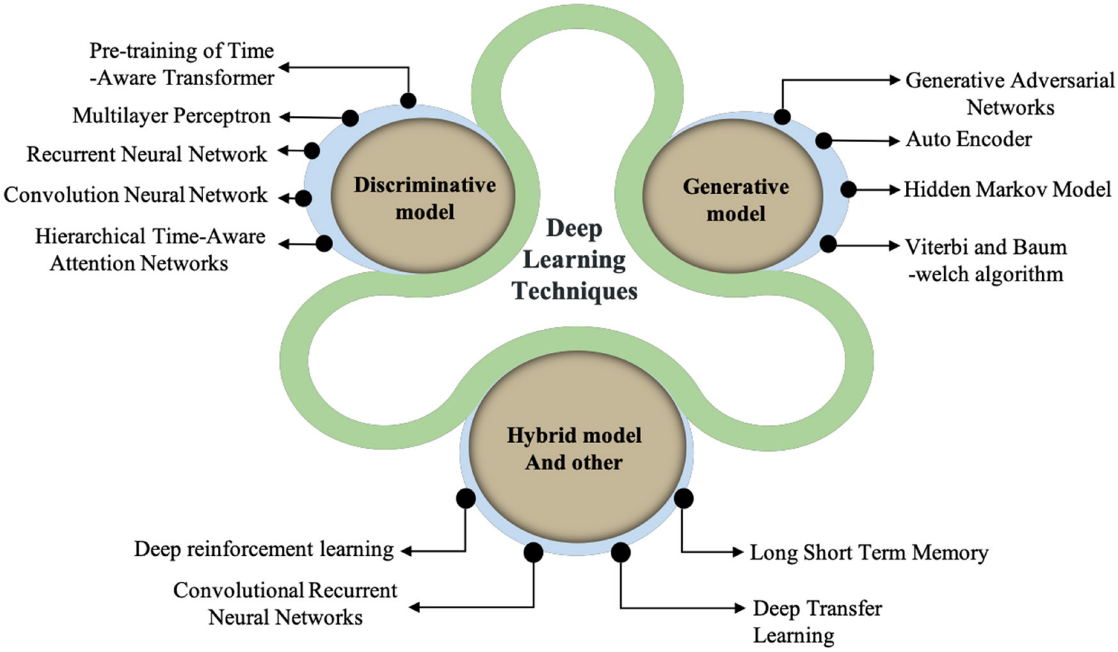

Figure 11 | DL techniques can be categorized into three main groups: (i) discriminative model, (ii) generative model, and (iii) hybrid model and others.

algorithms can be computationally intensive, requiring powerful hardware and specialized software to run effectively. DL is a powerful application of AI that has shown great promise in HI, particularly in the analysis of medical images and signals [115]. As the field continues to evolve, it will be important to address the challenges associated with data quality and computational resources to ensure that DL algorithms can be used effectively in clinical practice. In our research, we have discovered various techniques for DL as well as the outcomes of the proposed methods with the comparison methods of HI. The approaches utilized in the papers, as shown in Table 8 and the results of proposed DL algorithms, as shown in Table 9 are summarized as follows.

4.2.1. Convolutional Neural Network (CNN)

CNN has become an important tool in HI due to its ability to effectively process medical images and extract meaningful features. For instance, Bardou et al. [88] utilized a CNN-based model to accurately classify different types of skin lesions. Similarly, Maweu et al. [41] employed a CNN to diagnose diabetic retinopathy, achieving high accuracy rates. Also, Suganya and Rajaram [2] proposed an efficient CNN-based model for the diagnosis of breast cancer. The incorporation of CNNs into HI has contributed to the automation and standardization of medical image analysis, providing clinicians with more reliable and consistent diagnoses. However, these models may suffer from limitations such as overfitting, requiring large datasets and high computational power. Despite these limitations, CNNs have made significant contributions to the field of HI, offering innovative solutions to challenging problems in medical image analysis.

4.2.2. Generative Adversarial Network (GAN)

GANs have emerged as a powerful tool in HI due to their ability to generate realistic synthetic data from real-world data distributions. This has enabled a range of applications, including medical image generation, data augmentation, and anomaly detection. For example, Ren et al. [45] proposed a novel GAN-based approach for generating realistic medical images with fine-grained pathological patterns to aid in the diagnosis of diseases. Additionally, Rebello et al. [46] utilized GANs to reduce the imbalanced class distribution problem in EHRs, which can lead to inaccurate predictions and diagnoses. But GANs have limitations such as instability during training and the potential for generating biased or unrealistic data. Despite these challenges, the contributions and innovations of GANs in HI are significant, and ongoing research is focused on addressing their limitations to further improve their applicability.

4.2.3. Hidden Markov Model (HMM)

The HMM is a popular technique in HI due to its ability to capture temporal dependencies in data. This technique has been applied to various health-related tasks such as speech recognition, gene prediction, and the diagnosis of diseases. For instance, Ren et al. [118] proposed an HMM-based method for detecting vocal cord dysfunction using respiratory acoustic signals. Similarly, Shi et al. [115] employed for modeling patient behaviors in intensive care units to predict clinical outcomes. HMMs have also been used for detecting abnormal changes in EEG signals in patients with epilepsy [126]. Despite their popularity, this model suffers from some limitations, such as difficulties in handling long sequences and determining the optimal number of states. This method has made significant contributions to the field of HI, and its innovations continue to provide valuable insights into complex temporal data.

4.2.4. Viterbi and B & W Algorithm (VBWA)

The VBWA is a commonly used algorithm in HMMs and is increasingly being applied in HI. The VBWA is utilized in tasks such as disease diagnosis, drug discovery, and personalized medicine. For example, Singh et al. [119] proposed a new algorithm for cancer classification based on gene expression data using the

Table 8 | **Overview of various evaluation deep learning techniques and their applications**

Year	References	Convolution Neural Network	Generative Adversarial Networks	Hidden Markov Model	Viterbi and B & W Algorithm	Long Short Term Memory	Convolutional Recurrent Neural Networks	Deep Reinforcement Learning	Hierarchical Time-aware Attention Networks	Pre-training of Time-aware Transformer	Recurrent Neural Networks	Multilayer Perceptron	Auto Encoder	Deep Transfer Learning	Publication venue
2022	Ren et al. [45]		✓												ACM SIGKDD
	Sivasankari et al. [116]											✓			IEEE ICDCECE
	Lim et al. [34]												✓		IEEE JBHI
	Abbas [117]													✓	J. Intell. Fuzzy Syst.
2021	Men et al. [43]					✓									Expert Syst. Appl.
	Maweu et al. [41]	✓													Artif. Intell. Med.
	Ren et al. [118]			✓						✓					ACM SIGKDD
2020	Singh et al. [119]				✓										IEEE Access
	Luo et al. [120]								✓						ACM SIGKDD
	Mulani et al. [44]							✓							Springer
	Ma et al. [121]								✓						AAAI
2019	Suganya and Rajaram [2]	✓													Cluster Comput.
	Ma et al. [42]	✓													BMC Med. Inform. Decis. Mak.
	Spanig et al. [37]							✓							Artif. Intell. Med.
	Guo et al. [36]						✓								IEEE Access
	Shi et al. [115]			✓											ACM SIGKDD
	Khayyat et al. [122]				✓										IEEE SIEDS
2018	Bardou et al. [88]	✓													IEEE Access
	Faust et al. [123]					✓									Comput. Biol. Med.
	Van Steenkiste et al. [124]					✓									IEEE JBHI
	Su et al. [125]										✓				IEEE EMBS BHI
2017	Yu et al. [126]			✓											IEEE JBHI
	Ma et al. [87]										✓				ACM SIGKDD KDD
	Moreau et al. [127]										✓				IEEE JBHI
	Kavakiotis et al. [128]				✓										CSBJ
2016	Holzinger [129]							✓							Brain Inf.
	Rebello et al. [46]		✓												HIJ

Table 9 | Results of proposed deep learning algorithms

Reference	Purpose	Proposed methods results	Compared methods
Moreau et al. [127]	Detect nocturnal scratching events based on actigraphy data	RNN-Acc: 66.0%, Rec: 68.2%, Pre: 71.0%	BRNN
Bardou et al. [88]	Classify of breast cancer histology images	CNN-Acc: 97.80%, Rec: 97.57%, Pre: 97.68%	CNN, SIFT, DSIFT, SVM
Guo et al. [36]	Process diagnosis and interpretable disease	CRNN-Acc: 66.69%, Rec: 70.87%, Pre: 79.59%	RNN, RETAIN, Dipole
Luo et al. [120]	Classify hypertension in adolescents using the developed MLP model	MLP-ACC: 76.0%, Rec: 75.0%, Pre: 65.0%	ANN, RTF, SVM, BN
Men et al. [43]	Multi-disease prediction	LSTM-Acc: 87.9%, Rec: 84.2%, Pre: 92.0%	BRNN, T- LSTM, Hi- TANet
Ren et al. [118]	Effectively learn representations applied to various downstream tasks for electronic health data	RAPT-ACC: 96.6%, Rec: 96.4%, Pre: 95.5%	Trans, Hi- TANet, LSTM
Ren et al. [45]	Solving the data insufficiency problem	GAN-Acc: 76.1%, Rec: 84.5%, Pre: 63.9%	LSTM, GRU, HiTANet
Lim et al. [34]	Exploring characteristics of latent representations and exploiting LogR for diverse tasks including glucose forecasting, event detection, and temporal clustering.	AE-Acc: 91.1%, Rec: 92.7%, Pre: 89.5%	VAE, LogR
Abbas [117]	Individualized healthcare prediction	DTL-ACC: 87.02%, Rec: 50.82%, Pre: 53.17%	GRU, Transformers, T-LSTM

VBWA. The study showed that their proposed algorithm outperformed other existing algorithms in terms of accuracy and specificity. Other studies have used VBWA in analyzing EHRs data to predict patient outcomes [128]. However, one of the limitations of VBWA is its high computational complexity, which can lead to longer processing times [122]. Nevertheless, VBWA remains a promising tool in HI due to its ability to handle incomplete or noisy data and its potential for accurate prediction in various clinical scenarios.

4.2.5. Long Short Term Memory (LSTM)

LSTM is a powerful DL algorithm that has been extensively used in HI due to its ability to model and predict complex temporal sequences. It has been particularly effective in handling time-series data that exhibit long-term dependencies and patterns, making them useful in tasks such as disease progression modeling, patient monitoring, and clinical decision support. For example, Faust et al. [123] used LSTM models to automate the detection of pneumonia and other pulmonary diseases from chest X-rays, while Van Steenkiste et al. [124] used this method to predict the onset of diabetes in patients with obesity. Recently, Men et al. [43] proposed a multi-modal LSTM model that integrated clinical, genomic, and imaging data to improve the accuracy of brain tumor prognosis. Although this technique has demonstrated remarkable performance in various HI applications, its high computational cost and the need for large amounts of labeled data can limit its practicality. Nonetheless, their potential for enhanced disease diagnosis and personalized medicine makes them an area of continued interest and research.

4.2.6. Convolutional Recurrent Neural Network (CRNN)

CRNNs have emerged as a powerful tool in HI due to their ability to handle sequential data with varying lengths, such as EEGs, ECGs, and medical images. CRNNs combine the strengths of both convolutional and RNNs, allowing for the extraction of features from raw data while maintaining the temporal information of the data. The interpretable CRNN model proposed by Guo et al. [36] demonstrated its effectiveness in predicting the progression of Alzheimer's disease using longitudinal data from the alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. Similarly, Zihlmann [130] applied this technique for detecting arrhythmia using ECG signals and achieved high accuracy rates. Their study demonstrated the potential for improving automated arrhythmia detection in clinical settings. Other studies have also been used for seizure detection in EEGs and the classification of medical images. However, like other DL models, CRNN has limitations in terms of model interpretability and generalizability, and further research is needed to address these challenges.

4.2.7. Deep Reinforcement Learning (DRL)

DRL has a promising approach to solving complex decision-making problems in HI. DRL-based systems learn to maximize a reward function by iteratively taking actions in response to environmental states. For example, Spanig et al. [37] demonstrated the potential of DRL for personalized optimization of insulin therapy in patients with type 1 diabetes, while Holzinger et al. [129] discussed the importance of interactive ML for developing DRL-based clinical decision support systems. Similarly, Mulani et al. [44] showed the potential for optimizing medication doses in sepsis patients, highlighting its ability to handle complex and dynamic clinical environments. Despite these promising results, limitations remain, such as the need for large amounts of high-quality data and the interpretability of DRL-based models. The contributions and innovations of DRL in HI suggest a bright future for this approach to improving patient outcomes.

4.2.8. Hierarchical Time-aware Attention Network (HTAAN)

HTAANs effectively integrate temporal information and attention mechanisms into a hierarchical structure for improved performance in time series data analysis. For example, Luo et al. [120] proposed HTAANs for predicting medical events from EHRs using patient trajectories. Another, Ma et al. [121] used HTAANs to predict the mortality risk of sepsis patients using EHR data. The model was able to outperform other traditional ML models and demonstrated the potential of HTAANs in predicting patient outcomes in a clinical setting. The model was able to depict the intricate patterns of EHR data, outperforming other state-of-the-art models. HTAAN's ability to incorporate attention mechanisms at multiple levels and adaptively learn the relevance of each time step to the final prediction makes it a promising algorithm for various healthcare applications. Limitations of the algorithm include the need for large amounts of data and high computational requirements. However, the contributions and innovations of HTAANs suggest their potential for advancing HI research.

4.2.9. Pre-training of a Time-aware Transformer (PTT)

PTT is a novel DL algorithm that has shown promising results in various healthcare applications. PTT utilizes a transformer-based architecture with a pre-training stage that considers the temporal dynamics of medical data, making it suitable for tasks that require long-term dependencies. The pre-training process enables the model to learn from large-scale unlabeled data, which has been shown to improve its performance in downstream tasks. For example, Ren et al. [118] applied for predicting heart failure mortality, achieving superior results compared to other state-of-the-art models. Moreover, the model's interpretability was demonstrated by visualizing the attention weights of the temporal embedding, which helped identify relevant features for the prediction task. This algorithm has shown promising results, but its limitations include the need for large amounts of labeled data for fine-tuning and a relatively high computational cost during training. The contributions of PTT, such as its ability to capture temporal dynamics, make it a valuable addition to the toolbox of DL algorithms for healthcare applications.

4.2.10. Recurrent Neural Network (RNN)

RNN has become a widely used technique in the healthcare domain due to its capability of handling sequential data. It has been applied to various healthcare tasks such as disease diagnosis, patient monitoring, and medical image analysis. One study by Su et al. [125] proposed an LSTM, RNN model for the prediction of epileptic seizures, which outperformed other models. Another study by Ma et al. [87] used a dipole RNN to model dynamic brain connectivity for the detection of Alzheimer's disease. Additionally, Moreau et al. [127] utilized RNNs for the detection of arrhythmia from electrocardiogram signals. Despite the success of RNNs in healthcare, there are still limitations, such as their sensitivity to initial conditions and vanishing gradients. However, innovations such as gated recurrent units and attention mechanisms have been introduced to address these challenges and improve the performance of RNNs in healthcare applications.

4.2.11. Multilayer Perceptron (MLP)

MLP is an essential DL algorithm that has been widely used in HI due to its ability to classify and predict medical data with high accuracy. This is a feed-forward neural network model with many layers of neurons: an input layer, one or more hidden layers, and an output layer. In the context of HI, this technique has been utilized in a range of applications such as medical image analysis, disease diagnosis, and prediction of treatment outcomes. For instance, Sivasankari et al. [116] proposed an MLP-based algorithm for the classification of breast cancer using histopathological images, which achieved high accuracy and outperformed other traditional ML methods. The study demonstrated the potential of improving the accuracy and efficiency of a breast cancer diagnosis. However, despite its effectiveness, has limitations, such as its susceptibility to overfitting and the need for large amounts of labeled data. The contributions and innovations of HI research cannot be overlooked, and its applications are expected to continue expanding as more medical data becomes available for analysis.

4.2.12. Auto Encoder (AE)

AE is a type of unsupervised learning algorithm used in DL that has been increasingly used in HI for feature learning and anomaly detection tasks. The AE is capable of learning the most salient features of high-dimensional input data and generating new samples similar to the input data. This capability has made AE a valuable tool in various medical applications such as medical imaging analysis, EEG signal processing, and EHR analysis. For example, Lim et al. [34] proposed a multi-modal AE for COVID-19 diagnosis from X-ray and CT images, which showed better performance than single-modal models. The main limitations of AE are the need for a large amount of data and the difficulty in interpreting the learned features. Nonetheless, AE's potential for automated feature extraction and data generation has led to significant contributions in the field of HI, including improved diagnostic accuracy and faster analysis of medical data.

4.2.13. Deep Transfer Learning (DTL)

DTL has developed and is now a potent method in HI for leveraging the knowledge learned from pre-trained DL models and transferring them to a new task with limited labeled data. It has enabled the development of accurate and effective models for a wide range of healthcare applications, such as medical image analysis, EHR analysis, and disease diagnosis. For example, Abbas [117] proposed a hybrid model that combined the pre-trained weights of two deep neural networks to achieve better classification accuracy in predicting breast cancer recurrence. Also, Chen [51] proposed a DTL-based framework for detecting skin lesions using medical images, achieving state-of-the-art performance. However, one of the major limitations of DTL is the potential loss of task-specific features, which can negatively impact the model's performance. Despite this limitation has the potential to significantly advance the field of HI by improving the accuracy and efficiency of various medical applications.

5. DISCUSSION

The field of health informatics (HI) is rapidly expanding, and the use of artificial intelligence (AI) has the potential to change the way healthcare is supplied and managed. This systematic review aims to provide a complete overview of the current state-of-the-art in the application of AI in HI, as well as to suggest new possibilities and potential for future research.

5.1. Applications

AI, which is the process of computers displaying intellect as opposed to human intelligence, provides a number of possibilities for offering greater healthcare and clinical decision assistance in the field of HI [109,131,132]. AI has a broad spectrum of possibilities in this industry that have the potential to enhance patient outcomes, lower healthcare costs, and boost the effectiveness of healthcare delivery. Many sectors of HI have seen the promise of AI, including:

- **Medical diagnosis and decision-making:** This sector is a promising application of AI in HI that can assist healthcare professionals in making accurate diagnoses and treatment decisions. Machine learning (ML) algorithms, such as deep learning (DL) approaches, i.e., like recurrent neural networks (RNNs) and convolutional neural networks (CNNs), may examine patient data to find patterns and forecast the likelihood of certain diseases or disorders. These methods may be trained on massive datasets of medical pictures like X-rays and magnetic resonance imaging (MRI) [76]. Moreover, predictive modeling can also be used, which involves the use of ML algorithms to analyze patient data, such as electronic health records (EHRs), to predict the likelihood of certain outcomes, such as hospital readmissions or the onset of a particular disease [133]. The use of AI in medical diagnosis and decision-making has the potential to significantly improve patient outcomes through the provision of earlier, better, and more precise diagnoses, as well as personalized treatment plans. However, there are also potential ethical and regulatory concerns that need to be addressed, such as ensuring the transparency and fairness of AI algorithms and protecting patient privacy [134].
- **Drug development and personalized medicine:** AI is being used to simplify the drug development process and personalize medicine by predicting the efficacy and safety of drug candidates and customizing treatment regimens for particular patients based on their unique genetic composition and health history. AI techniques like ML are used to evaluate enormous volumes of data from diverse sources, like clinical trials, EHRs, and genetic data, in order to find prospective drug candidates and forecast their safety and efficacy. Additionally, AI can be used to identify patient subgroups with unique characteristics that may respond differently to a particular treatment, enabling healthcare professionals to personalize treatment plans. This can result in better patient outcomes and a more efficient medication development process [135,136].
- **Patient monitoring and management:** AI-powered monitoring systems have emerged as a promising technology for patient monitoring and management. These systems utilize advanced algorithms to process patient data, identify patterns and trends, and generate alerts for healthcare professionals in real-time. By continuously monitoring patients' health status, AI-powered systems can detect potential issues before they become serious, allowing for early intervention and improved patient outcomes. This can lead to a reduction in healthcare costs by preventing hospital readmissions and other complications. A study conducted by Pekmezaris et al. [137] demonstrated the effectiveness of an AI-powered remote monitoring system for patients with heart failure, which reduced hospitalizations by 70%. Similarly, Parasa et al. [138] discovered that AI-powered monitoring systems enhanced clinical outcomes for patients with chronic conditions, including diabetes and hypertension. These studies highlight the potential of AI-powered monitoring systems to transform patient care and improve health outcomes.
- **Healthcare system optimization:** AI offers enormous promise for stream-lining healthcare systems and enhancing operational efficiency. One application of AI in healthcare systems is the use of predictive analytics to forecast patient demand and allocate resources accordingly. For instance, a study by Raita et al. [139] demonstrated that ML models could predict emergency department visits with high accuracy, thereby allowing hospitals to allocate their resources effectively. Additionally, Natural language processing (NLP) can be employed to automate administrative tasks and improve communication between healthcare providers. An example of this is the study by Cai et al. [140], which utilized NLP to automate clinical documentation tasks in radiology departments, resulting in a significant reduction in time spent on documentation. These applications of AI can greatly benefit healthcare systems in terms of resource allocation and streamlining administrative tasks, ultimately improving patient care and outcomes.
- **Personalized medicine:** AI has the potential to transform healthcare by enabling tailored treatments. One way to achieve this is through the analysis of patient records, including genomics and EHR, to create personalized treatment plans tailored to individual patients. A study by Carruth et al. [141] demonstrated the use of ML algorithms to analyze genomic and EHR data for personalized treatment of patients with inflammatory bowel disease. Another study by Torkamani et al. [142] used AI to analyze genomic data to predict drug response and identify potential adverse drug reactions. By adapting treatment strategies to individual patients based on their unique traits and medical history, these AI applications in personalized medicine can lead to better patient outcomes.
- **AI for drug discovery:** The development and discovery of drugs is an intensive and costly procedure that involves the identification of new chemicals with the potential to heal certain conditions. AI can play a vital role in this process by analyzing large datasets to identify possible drug candidates and predict their efficacy. ML algorithms can be used to sift through vast amounts of chemical data and identify patterns that may indicate the likelihood of a molecule is an effective drug. Additionally, AI can be used to predict the toxicity and side effects of drugs and optimize dosages. One example of the successful application of AI in drug discovery is the identification of new treatments for Alzheimer's disease using DL algorithms to analyze large genomic datasets [143]. Another example is the development of new anti-cancer drugs using AI to analyze large databases of gene expression data and identify molecules that target specific cancer cells [144].
- **Image analysis:** AI has grown in importance in healthcare, notably in the field of medical picture processing. AI can greatly improve the effectiveness of diagnostic medical analyses, such as identifying cancers in X-rays or anomalies in MRI scans, by allowing clinicians to detect subtle differences in medical images that may not be easily visible to the human eye. CNNs and DL-based methods have shown great promise in the detection and classification of breast cancer, brain tumors, lung nodules, skin lesions, and retinal abnormalities. Recent studies have investigated the potential of AI in these areas, demonstrating the accuracy and efficiency of DL algorithms in medical image analysis. For example, studies by Esteva et al. [76], Golan et al. [145], and Kavitha et al. [146]

show the potential of DL-based algorithms for the detection of skin cancer, lung nodules, and breast cancer, respectively. These AI technologies have the possibility to improve diagnostic accuracy while decreasing healthcare costs.

- **Predictive analytics:** Predictive analytics is a critical use of AI in health-care informatics with the potential to transform patient care. It involves using ML algorithms to analyze large datasets and identify patterns, which can help predict future health outcomes and identify patients at risk for specific problems. This enables early intervention and treatment, leading to improved patient outcomes and reduced healthcare costs. In a recent study, researchers used predictive analytics to identify patients at risk of hospital readmission and developed a personalized care plan to reduce the risk [147]. Another study used ML algorithms to predict the onset of diabetes and developed a personalized intervention plan for at-risk individuals, resulting in a significant reduction in the incidence of diabetes [148]. These studies demonstrate the potential of predictive analytics for improving patient care and reducing healthcare costs. However, successful predictive analytics application in healthcare necessitates the integration of EHRs, clinical decision support systems, and patient interaction technologies. It also requires careful consideration of ethical, legal, and social issues.
- **Telemedicine:** Telemedicine has gotten a lot of focus in recent years, particularly during the COVID-19 epidemic, because it offers an alternative to in-person consultations, lowering the danger of virus transmission [149]. AI-powered chatbots and virtual assistants are widely used in telemedicine, offering personalized health advice, symptom checking, and assistance in scheduling appointments. The development of these AI applications is based on NLP and ML algorithms, which allow chatbots to simulate human-like conversation and understand patient queries accurately [150]. For example, the AI-powered chatbot developed by Babylon Health can provide patients with advice on common ailments, such as coughs and colds, and refer them to a healthcare professional if necessary. Additionally, virtual assistants like Siri and Alexa can also help patients manage their health by providing reminders for medication, tracking their activity, and monitoring vital signs [150]. These AI-powered telemedicine applications can reduce the workload of healthcare providers, improve access to care, and enhance patient satisfaction.
- **Health monitoring:** The development of AI in HI has transformed health monitoring by enabling health monitoring capabilities with a wide range of applications. The critical area of health monitoring is where AI shows its promise. AI algorithms may identify major changes in a patient's health state by using physiological markers like heart rate, blood pressure, and blood sugar levels that are collected by wearable tech and medical equipment. Healthcare professionals may quickly intervene and give timely treatment thanks to this early diagnosis, which ultimately improves patient outcomes. For instance, research by Topol et al. [151] demonstrating the effectiveness of AI-based monitoring in identifying atrial fibrillation, a common heart arrhythmia, by analyzing electrocardiogram (ECG) data. Additionally, Porumb et al. [152] created an AI-driven system called that uses data from continuous glucose monitoring to identify hypoglycemic episodes in people with type 1 diabetes. These instances show how AI-driven health monitoring systems have the ability to provide individualized and efficient treatment, with early detection skills that considerably improve health outcomes.
- **Clinical decision support:** One of the most common uses of AI in the field of HI is clinical decision assistance. Healthcare professionals may benefit greatly from the use of AI algorithms by assessing patient data and providing evidence-based suggestions for diagnosis and treatment. These techniques largely depend on the use of ML algorithms that have been trained on large patient datasets in order to recognize patterns and make predictions. For instance, IBM watson for oncology (WFO) is an excellent algorithm that uses ML and NLP to evaluate medical data and propose treatments for cancer patients [153]. DL is also used by the DeepMind Health system to evaluate medical pictures, assisting radiologists in spotting clinical signs of disorders like diabetic retinopathy [154]. Despite the fact that clinical decision support using AI is still in its infancy, it is crucial to recognize the problems that still need to be solved in order to guarantee the security and efficiency of these systems. Nevertheless, further study in this field has a great deal of promise for improving patient outcomes and expediting healthcare delivery [155].
- **Healthcare robotics:** Medical robots are becoming an increasingly significant part of patient assistance in the healthcare industry, working alongside medical staff. Exoskeleton robots, which might assist paralyzed individuals recover their capacity to move and attain more independence, are among the most promising examples [156]. These prosthetic limbs may provide more responsiveness and precision than normal body parts by adding sensors. In order to construct a smart prosthesis, they may also be coated with bionic skin and connected to the user's muscles. Medical robots are also beneficial in procedures like surgery and rehabilitation. The Hybrid Assistive Limb (HAL) exoskeleton created by Cyberdyne is one famous example. This equipment is specially made to help those who have lower limb abnormalities brought on by spinal cord injuries and strokes. It may react with exact motions at the joint by employing sensors put on the skin to detect electrical impulses coming from the patient's body, allowing more efficient and successful rehabilitation [157]. Medical robots have the potential to significantly improve patient outcomes and revolutionize healthcare as medical technology develops.

5.2. Challenges

The proposed AI-based models for HI offer many benefits, but they also bring some drawbacks that need to be considered. Firstly, these models are only applicable to a certain portion of the population, limiting their effectiveness and reach. Secondly, achieving absolute precision is not possible due to their limitations. Moreover, HI relies entirely on technology, making susceptible to constrains of modelling and technological infrastructure. Finally, there are several privacy and security concerns in the use of AI in health. Due to their size, inability to buy it, and lack of ability to utilize it, a sizable portion of the population is not allowed access to HI systems.

The success of these HI models depends on the user or patient's active involvement. Patient data loss or data misplacement is a continuous risk, affecting the continuity of historical records. Furthermore, the confidentiality and security of the health data stored within HI solutions can encounter various challenges. In such situations, there is a potential threat of unauthorized access and sharing of private data, compromising its privacy and confidentiality. Some of the potential issues that may arise while integrating AI in HI include:

- **Lack of data quality and standardization:** High-quality, standardized data is essential for the effective implementation of AI systems. However, in many cases, data is incomplete, inconsistent, or biased, which can lead to erroneous forecasts and choices.
- **Privacy and security concerns:** The use of AI in healthcare creates serious privacy and security concerns. AI systems require access to sensitive patient data, which must be carefully protected to minimize security breaches.
- **Ethical and legal considerations:** There are various legal and ethical considerations associated with the use of AI in healthcare. For example, AI algorithms may be biased or discriminatory, and the use of AI may raise questions about accountability and liability in the event of errors or malfunctions.
- **Technical challenges:** AI systems can be complex and require significant technical expertise to develop and implement. The need for skilled professionals and technological resources may pose a barrier to the widespread adoption of AI in healthcare.
- **Integration and adoption:** Implementing AI in clinical settings requires overcoming technical, organizational, and cultural barriers. Investigators must devise techniques for effectively integrating AI technologies into existing systems and encouraging healthcare providers to use them.

5.3. Future Directions

AI has the ability to completely change HI and healthcare delivery. From the standpoint of HI, many benefits of this combination are given. Specifically, all health-related technology applications and fundamental technologies like computation, monitoring, and connectivity are thoroughly presented. It also illustrates how different ML technologies fit into the existing HI paradigm. However, many difficulties have to be overcome in order to fully exploit the benefits of AI in health. The following are some of the key areas where future research efforts can be directed:

- **Development of robust and interpretable AI models:** One of the most difficult aspects of AI models is that they can be black boxes, making it impossible to understand how they arrived at their predictions. Future research efforts should focus on developing AI models that are not only accurate but also transparent and interpretable, allowing clinicians to trust and understand the decisions made by these models.
- **Integration of AI into clinical workflows:** AI tools and systems need to be seamlessly integrated into clinical workflows to ensure their effective adoption and use. Future research should explore ways to integrate AI into clinical decision-making processes and workflows, such as EHR systems, to ensure that AI is used effectively and efficiently.
- **Ethical and legal considerations:** AI raises a number of ethical and legal challenges that must be addressed in order to assure its responsible and ethical use. Future research should look towards ways to ensure that AI is used in a fair, transparent, and patient-centered manner that respects patient privacy and autonomy.
- **Data quality and availability:** The quality and quantity of data utilized to train AI models has a significant impact on their performance. Future research should focus on developing methods for improving the quality and availability of healthcare data to ensure that AI models can be trained effectively and accurately.
- **Evaluation of AI in real-world settings:** While many promising studies on the application of AI in healthcare have been conducted, additional study is required to assess the impact of AI in real-world settings. Large-scale studies should be conducted in the future to measure the usefulness of AI in improving clinical outcomes and lowering healthcare expenditures.
- **Development of new AI algorithms:** As AI technology progresses, more advanced algorithms are required to improve the precision and effectiveness of HI systems.
- **Integration with other technologies:** AI integration with other technologies, such as blockchain and the Internet of Things, has the potential to improve the efficiency and security of HI systems.
- **Clinical implementation and adoption:** While there is growing interest in AI-based HI applications, their implementation and adoption in clinical practice remain limited. Future research could focus on identifying barriers to adoption and developing strategies to overcome them.
- **Collaboration between disciplines:** HI is a multidisciplinary field, and future research could benefit from greater collaboration between researchers from different disciplines, such as computer science, medicine, and public health.

6. CONCLUSION

The most significant technical development in recent research is the approach known as health informatics (HI), which utilizes various applications and technologies for health treatments. Likewise, the application of artificial intelligence (AI) in HI is viewed as a significant achievement of modern healthcare systems. In this work, we investigate the present state of AI applications in HI, with an emphasis on the influence of AI on participatory health from both the patient and clinician perspectives. Several more advantages of this combination for HI are highlighted. The competency domains of HI, include information technology, health information systems, telemedicine and m-Health, health information security and privacy, consumer HI, and clinical informatics which are explained in detail. Future studies might include a full assessment of the based on previous AI applications and merging them with other digital health-related software or data with the goal of assessing their effectiveness concerns on these systems. By using AI's potential while upholding moral and responsible standards, we can create a more efficient and effective healthcare system that benefits both patients and healthcare providers.

DECLARATIONS

Ethical Approval

Not applicable.

Conflict of Interest

The authors declare that they have no conflicts of interest.

Authors' Contribution

MEH and MJI wrote the main manuscript text and MRI guided MEH and MJI to write the whole research article. Additionally, all authors reviewed the manuscript.

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