BMC Digital Health

RESEARCH

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Artificial intelligent tools: evidence-mapping on the perceived positive effects on patient-care and confidentiality

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Abstract

Background Globally, healthcare systems have always contended with well-known and seemingly intractable challenges like safety, quality, efficient and effective clinical and administrative patient-care services. To firmly confront these and other healthcare challenges, the World Health Organisation proposed a full adoption of artificial intelligence (AI) applications into patient care to stimulate efficiency and guarantee quality in patient management.

Purpose This review aimed to establish the extent and type of evidence of the positive effects of the use of AI tools in patient care. Thus, the review mapped evidence by using articles published between January 1, 2010, and October 31, 2023.

Methods Consistent with the protocol by Tricco et al., a comprehensive literature search was executed from Nature, PubMed, Scopus, ScienceDirect, Dimensions, Web of Science, Ebsco Host, ProQuest, JStore, Semantic Scholar, Taylor & Francis, Emeralds, World Health Organisation, and Google Scholar. Upholding the inclusion and exclusion standards, 95 peer-reviewed articles were included in this review.

Findings We report that the use of AI tools can significantly improve the accuracy of clinical diagnosis to guarantee better patient health outcomes. AI tools also have the ability to mitigate, if not eliminate, most of the factors that currently predict poor patient outcomes. Furthermore, AI tools are far more efficient in generating robust and accurate data in real time and can help ease and accelerate workflow at healthcare facilities.

Conclusion If properly integrated into the healthcare system, AI will help reduce patients' waiting time and accelerate the attainment of Sustainable Development Goals 3.4, 3.8, and 3.b. We propose that AI developers collaborate with public health practitioners and healthcare managers to develop AI applications that appreciate socio-cultural dimensions in patient care.

Keywords Artificial Intelligence, Computer vision system, Knowledge representation, Machine intelligence, Patient data privacy, Privileged communication

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Introduction

The global healthcare system is challenged with the scarcity of critical healthcare professionals, changes in disease patterns, high cost of healthcare, adverse effects of climate change, pandemics, and access and equity issues, among others [1–4]. Historically, the healthcare system has always contended with well-known and seemingly intractable challenges, including safety, treatment-diagnosis mismatch, misdiagnosis, under and over-prescription, inaccurate and incomplete patient records, inadequate resources and workforce to sustain the ever-stretched patient-care services [5, 6]. Given that the deadline set for the realisation of the Sustainable Development Goals (SDGs) is fast approaching, healthcare managers are adopting several strategies to fix the challenges sustainably [3, 7]. Considering that there is no quick fix to the numerous sets of healthcare challenges, the World Health Organisation (WHO) proposed, in addition to other interventions, a full integration of artificial intelligence (AL) tools in healthcare to stimulate efficiency and accelerate the realisation of the health-related SGDs [3, 7, 8].

AI tools are a set of technologies with computerised features that have the capacity to simulate intelligent human behaviours [5, 8]. These tools possess speed, huge data storage and processing capacity, are reliable, interoperable with other technological systems, and by far more accurate in their interpretations and patients' diagnoses [9, 10]. When effectively combined with human reasoning, AI tools have the ability to accurately establish patterns and complex correlations subtly in large and high-dimensional datasets that often escape the traditional techniques [8, 11].

Though the full adoption of AI tools into healthcare is yet to be realised, there is evidence of the wide application of AI tools in patient care globally [10, 12, 13]. So far, AI applications in patient care are getting more sophisticated, effective, and efficient in supporting clinical and administrative decisions [2, 12]. Regardless of the level of AI use in patient care across the globe, these intelligent machines appear to be super-supportive and could redefine the future of healthcare and change its face for the better [10, 14, 15]. The utilisation of AI and other new technologies saw a surge globally during the Sars-Cov-2 pandemic [16–18]. For instance, various AI and new technological platforms and devices were utilised to provide continuous and essential healthcare services to patients, including predicting mortality during the pandemic [16–18]. Some of these mediums and devices include mobile-based self-care, video conferencing, virtual healthcare, tele-monitoring, tele-medicine, tele-consulting, tele-intensive care unit, e-consult, tele-radiology, virtual visits, and telesurgical services [16–18]. At this point, the patient remains the ultimate "subject" in this whole discourse and is in whose best interest AI tools are deployed in the healthcare system [2, 19, 20].

While there is growing recognition of the utility of AI tools in patient care, their coverage in the developing world is rather on a small scale [21–23]. So far, Asia, North America, and Europe appear to be the continents with the fastest AI coverage and with widespread application in patient-care services [13, 22, 24]. Though these continents are far from realising full adoption of AI applications in all aspects of their healthcare systems, there are modest gains across these continents [25, 26]. For instance, funding for research projects in AI adoption in healthcare through the European Union Horizon 2020 scheme shot up between 2014 and 2020 [27]. Moreover, the European Commission developed several ethicolegal instruments to regulate and guarantee the responsible design and use of AI systems in patient care and beyond [22, 27].

In North America, for example, AI tools are currently being applied in the management of cancer, hypertension, cerebrovascular accidents and conditions, and in obstetrics as well as paediatric care services [6, 9, 27]. The other continents, including Australia, South America, and Africa, have also recorded modest successes in the application of AI tools in their healthcare systems [7, 13, 22, 28]. Though records exist about AI applications in invasive and non-invasive procedures in these continents, especially in Africa, their use is more associated with smart devices aided by applications such as AiCure and a gamut of AI ChatBots [19, 20, 22].

Despite the growing application of AI in other fields worldwide, there seems to be inadequate empirical account, especially evidence synthesis, to clearly establish common themes and concepts across existing literature on the use of AI tools in patient care [13, 15, 20]. Specifically, there is inadequate evidence mapping on how the use of AI tools in healthcare is positively impacting patient care globally [2]. Meanwhile, these pieces of evidence are essential for developing policy and evidence-based integration of AI tools into healthcare for improved patient outcomes. Moreover, the role of AI in achieving SDG 3.4 (attainment of universal health coverage, including access to quality essential healthcare services, medicines and vaccines for all) by 2030 is not clear [3, 7, 8]. Certainly, AI would be a critical resource in this global quest, and reviews collating such pieces of evidence are of urgent need. Therefore, this review aimed to fill this research gap by mapping the existing evidence of the positive effects of the use of AI tools in patient care.

Methods

Study design and search strategy

We examined, synchronised, and analysed peer-reviewed articles using Tricco et al. [29] guidelines. This includes developing and examining the purpose of the study, crafting, reviewing, and examining the research questions, and then identifying and discussing the search terms. The other guidelines include identifying and exploring relevant databases, downloading articles, data mining, organising and synthesising results and carrying out consultation. Five questions defined the review, including, "what are the potential positive effects of AI applications on (1) healthcare data, (2) diagnostic decisions, (3) patient-care, (4) medical errors, and (5) medical emergencies?".

To inject rigour and comprehension into the search process, we first explored PubMed for Medical Subject Heading (MeSH) terms on the topic (see Table 1). The MeSH terms were validated by a research librarian with over 10 years of working experience in the university. Search for articles was executed at two levels based on the MeSH terms. First, the search terms "Confidentiality" or "Artificial Intelligence" yielded a total of 4,512 articles. Second, the search was based on 30 MeSH terms and also produced a total of 1,688 articles (see Fig. 1 and Table 1). The search covered studies conducted between January 1, 2010, and October 31, 2023. The current study was executed between January 1 and October 31, 2023.

This review was conducted in consistent with the Preferred Reporting Items for Reviews and Meta-Analyses extension for Scoping Reviews—PRISMA-ScR [29, 30]. Through a detailed and an exhaustive data screening process, all duplicate articles were kept in a folder and later deleted. Many of these deleted articles were considered incoherent with the inclusion standards (as described below). The first level screening was executed by five authors (FSA, SM, RVK, LAA, and IST). However, where the suitability of an article was in contention, that article was referred to four other authors (EWA, CES, VKD, and NNB) for further assessment until consensus attained. To ensure comprehension and rigour in the search process, citation chaining was done on all full-text articles that met the inclusion standards to identify relevant additional articles for further assessment.

Data sources

We searched for peer-reviewed articles from the following databases/publishers/search engines: Nature, PubMed, Scopus, ScienceDirect, Dimensions, Web of Science, Ebsco Host, ProQuest, JStore, Semantic Scholar, Taylor & Francis, Emeralds, World Health Organisation, and Google Scholar (see Fig. 1 and Table 1). Through a comprehensive and independent assessment of various databases/publishers/search engines conducted by five authors (EWA, VKD, CES, SM, and NNB), the sources mentioned above were found to contain a very good number of relevant articles on the subject under review.

Table 1 Search strategy

Search strategy item	Search strategy
Databases/Search Engines/Publishers	Nature (164), PubMed (157), Scopus (83), ScienceDirect (185), Dimensions (118), Web of Science (63), Ebsco Host (51), ProQuest (77), JStore (93), Semantic Scholar (81), Taylor & Francis (96), Emeralds (94), World Health Organisation (18), and Google Scholar (408)
Language filter	English
Time filter	January 1, 2010 to October 31, 2023
Spatial filter	Worldwide
MeSH terms used	**1. Confidentiality –** "Entry Terms" OR "Secrecy" OR "Privileged Communication" OR "Communication, Privileged" OR "Communications, Privileged" OR "Privileged Communications" OR "Confidential Information" OR "Information, Confidential" OR "Privacy of Patient Data" OR "Data Privacy, Patient" OR "Patient Data Privacy" OR "Privacy, Patient Data" **2. Artificial Intelligence – "**Intelligence, Artificial" OR "Computational intelligence" OR "Intelligence, Computational" OR "Machine Intelligence" OR "Intelligence, Machine" OR "Computer Reasoning" OR "Reasoning, Computer" OR "AI (Artificial Intelligence)" OR "Computer Vision Systems" OR "Computer Vision System" OR "Systems, Computer Vision" OR "System, Computer Vision" OR "Vision System, Computer" OR "Vision Systems, Computer" OR "Knowledge Acquisition (Computer)" OR "Acquisition, Knowledge (Computer)" OR "Knowledge Representation (Computer)" OR "Knowledge Representations (Computer)" OR "Representation, Knowledge (Computer)"
Inclusion criteria	Articles must be AI and health-related, primary research and conducted in the English Language, applied either quantitative, qualitative, or mixed methods. In addition, the articles must provide details on perceived positive effects of AI use in healthcare, and conducted between January 1, 2010 and October 31, 2023. Again, articles must provide details on author(s), purpose, methods, country, and conclusion
Exclusion criteria	Articles on AI and health but did not touch on perceived positive effects of AI tools use in healthcare, reviewed articles on AI use in health, and articles on AI and health conducted in languages other than the English Language. Furthermore, abstracts, opinion pieces, short reports, incomplete articles, commentaries, grey literature, and media reports on AI and health were also ignored

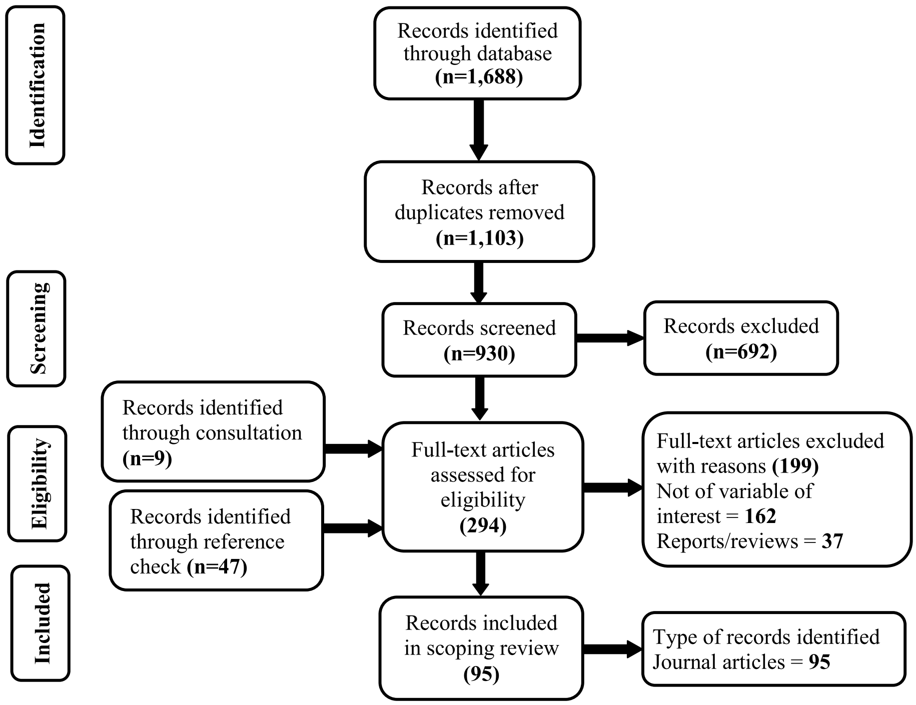

Fig. 1 PRISMA flow diagram

Study selection

A random sample of 12 titles and abstracts screened independently by four authors (EWA, NNB, CES, and SM) was used to standardise the inclusion and exclusion criteria. Weekly virtual and in-person meetings were held to discuss and reconcile disagreements and clarify eligibility among the four authors (EWA, NNB, CES, and SM) and the fifth author (VKD). Before progressing to full-text screening, authors ensured that all differences concerning the selection of articles were resolved by five authors (EWA, NNB, CES, SM, and VKD). Three authors (EWA, NNB, and CES) independently screened the articles before data extraction commenced.

Data extraction and thematic analysis

All authors carried out data extraction independently. Four authors (CES, RVK, LAA, and IST) extracted data on "authors, purpose, methods, and country," while five authors (EWA, VKD, FSA, SM, and NNB) extracted data on "perceived positive effects and conclusions" (see Table 2).

In consonance with Cypress [126] and Morse [127], thematic analysis was done by six authors (EWA, VKD, CES, SM, RVK, and NNB). Thus, data were coded until themes emerged directly from the data, in line with the stated research questions [127–129]. Our analysis included reading over and over to familiarise ourselves with the data, identifying candidate codes, identifying and assessing emerging themes. Additionally, emerging themes were reviewed, clearly named and defined. However, where doubt occurred, we extensively discussed till consensus was established. Finally, a qualitative report was developed and extensively reviewed to guarantee internal and external homogeneity of the themes.

Quality rating

We conducted quality ratings on all candidate articles in line with the guidelines provided by Tricco et al. [29]. That is, the shortlisted articles must have a research background, aim, context, clear method, sampling technique, data collection and analysis, reflectivity, value of research, and ethics. Therefore, all candidate articles were examined and scored according to the majority of the sections. Thus, articles that scored "A" had little or no limitations, "B" had some limitations, "C" had substantial limitations but carried some relevance, and "D" had substantial flaws that could undermine the validity of the study as a whole, so such articles were not used for this review [29].

Findings

We explored previous studies conducted from January 1, 2010, to October 31, 2023, on the positive effects of AI tools on patient care. A total of 1,688 articles were screened, of which 527(31%) discussed the use of AI applications in healthcare. Upon further assessment of the 527 articles, 95(18%) met the inclusion standards and were used

Table 2 Extracted data

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
1	Al'Aref et al. (2019) [31]	Using the New York Percutaneous Coronary Intervention Reporting System to elucidate the determinants of in-hospital mortality in patients undergoing percutaneous coronary intervention	Quantitative	North America	1. Accurate diagnosis 2. Improved referrals	High accuracy predictive potential for in-hospital mortality in patients undergoing percutaneous coronary intervention
2	Al'Aref et al. (2020) [32]	Culprit Lesion (CL) precursors among Acute Coronary Syndrome (ACS) patients based on computed tomography-based plaque characteristics	Quantitative	North America	1. Accurate diagnosis 2. Saves time	A boosted ensemble algorithm can be used to predict culprit lesion from non-culprit lesion precursors on coronary Computed Tomography Angiography (CTA)
3	Aljarboa and Miah (2021) [33]	Perceptions about Clinical Decision Support Systems (CDSS) uptake among healthcare sectors	Qualitative	Asia	1. Improved quality of care 2. Improved patient health outcomes 3. Reduced patient waiting time	Patients' confidence and diagnostic accuracy were new determinants of CDSS acceptability that emerged in this study
4	Aljarboa et al. (2019) [34]	Acceptance and intention of using Clinical Decision Support Systems (CDSS)	Qualitative	Asia	1. Improved quality of diagnosis 2. Reduction in medical errors 3. Reduced cost of care 4. Improved patient waiting time	Participants were positive that AI tools would contribute positively to patients care
5	Al-Zaiti et al. (2020) [35]	Machine learning-based methods for the prediction of underlying Acute Myocardial Ischemia in patients with chest pain	Quantitative	North America	1. Improved patient outcomes 2. Prompt referrals 3. Accurate diagnosis 4. Improved workflow	Machine learning model outperformed both commercial interpretation software and experienced clinician interpretation
6	Alumran et al. (2020) [36]	Electronic Canadian Triage and Acute Scale (E-CTAS) utilisation in emergency department	Quantitative	Asia	1. Very useful during emergency care 2. Improved patient health outcome	Years of nursing experience moderated the utilisation of E-CTAS
7	Amarbayasgalan et al. (2019) [37]	Deep learning-based model, Reconstructive Error (RE) based Deep Neural Networks (DNNs) to predict risk of developing Coronary Heart Disease (CHD)	Quantitative	Asia	1. Improved diagnostic capacity 2. High predictive capacity	The autoencoder (AE)-DNNs outperformed regular machine learning-based classifiers for coronary heart disease risk prediction
8	Ayatollahi et al. (2019) [38]	Positive Predictive Value (PPV) of Cardiovascular Disease using Artificial Intelligence Neural Network (ANN) and Support Vector Machine (SVM) algorithm and their distinction in terms of predicting Cardiovascular Disease	Quantitative	Asia	Improved diagnosis	The SVM algorithm presented higher accuracy and better performance than the ANN model and was characterised by higher power and sensitivity
9	Baskaran (2020) [39]	Using machine learning to gain insight into the relative importance of variables to predict obstructive Coronary Artery Disease (CAD)	Quantitative	North America	High potential for accurate diagnosis	Machine learning model showed BMI to be an important variable, although it is currently not included in most risk scores

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
10	Betriana (2021b) [40]	Interactions between healthcare robots and older persons	Qualitative	Asia	Improved quality of care	Interaction between healthcare robots and older people may improve quality of care
11	Beunza et al. (2019) [41]	Machine Learning (ML) algorithms for predicting clinical events in terms of their internal validity and accuracy	Quantitative	Europe	Improved diagnostic, prognostic, and therapeutic tools	Machine learning algorithms can reinforce the diagnostic and prognostic capacity of traditional regression techniques
12	Blanco et al. (2018) [42]	Barriers and facilitators related to uptake of Computerised Clinical Decision Support (CCDS) tools as part of a Clostridium Difficile Infection (CDI) reduction bundle	Qualitative	North America	Standardisation and error reduction	Findings shaped the development of Clostridium Difficile Infection reduction bundle
13	Borracci et al. (2021) [43]	Application of Neural Network (NN) algorithm-based models to improve the Global Registry of Acute Coronary Events (GRACE) score performance to predict in-hospital mortality and acute Coronary Syndrome	Quantitative	South America	1. Improved diagnosis 2. Improved turnaround time	Treatment of individual predictors of GRACE score with NN algorithms improved accuracy and discrimination power in all models
14	Bouzid et al. (2021) [44]	Consecutive patients evaluated for suspected Acute Coronary Syndrome	Quantitative	North America	1. Improved turnaround time 2. Improved diagnosis	A subset of novel electrocardiograph features predictive of acute coronary syndrome with a fully interpretable model highly adaptable to clinical decision support application
15	Catho et al. (2020) [45]	Adherence to antimicrobial prescribing guidelines and Computerised Decision Support Systems (CDSSs) adoption	Qualitative	Europe	Improve clinicians' adherence to guidelines and patient care	Features that could improve adoption include friendliness, ergonomics, transparency of the decision-making process and workflow
16	Cho (2020) [46]	Deep learning models to automatically classify Cervical Neoplasms on cloposcopic photographs	Quantitative	Asia	Early detection of disease	Provide a better potential of detecting high-risk lesions than previously reported
17	Chow et al. (2015) [47]	Physicians' perceptions and attitudes toward antibiotic Computerised Decision Support Systems (CDSS) recommendations for empirical therapy	Mixed	Asia	Confidence in the credibility of CDSS recommendations	Physicians would prefer to rely on their own or clinical team's decision over CDSS recommendations in complex patient situations when the antibiotic needs are not met
18	Davari Dolatabadi et al. (2017) [48]	Automatic diagnosis of normal and Coronary Artery Disease conditions using Heart Rate Variability (HRV) signal extracted from electrocardiogram	Quantitative	Asia	1. Improved data quality 2. Reduced cost of care	Methods based on the feature extraction of the biomedical signals are an appropriate approach to predict the health situation of patients

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
19	Davis (2020) [49]	Machine Learning (ML) algorithm for marking Computer Tomography (CT) head examinations pending interpretation as higher probability of intracranial haemorrhage (ICH), on metrics across healthcare system	Quantitative	North America	1. Reduced waiting time 2. Improved patient's condition 3. Quality of diagnosis improved	There was significant reduction in length of stay for patients without ICH, but not for emergency department patients with intensive care unit
20	Dogan et al. (2018) [50]	Examined whether similar machine learning approaches could be used to develop a similar panel to predict Coronary Heart Disease (CHD)	Quantitative	North America	Accurate and improved diagnosis	The AI tool is more sensitive than conventional risk-factor based approaches, and performs well in both males and females
21	Du et al. (2020) [51]	Using high-precision Coronary Heart Disease (CHD) prediction model through big data and machine-learning	Quantitative	Asia	1. Accurate and improved diagnosis 2. Real time diagnosis	Accurate risk-prediction of coronary heart disease from electronic health records is possible given a sufficiently large population of training data
22	Elahi et al. (2020) [52]	Traumatic Brain Injury (TBI) prognostic models	Mixed	Africa	Very effective in patient assessment at the triage especially in resource-limited settings	Addressed unmet needs to determine feasibility of TBI clinical decision support systems in low-resource settings
23	English et al. (2017) [53]	Application of a modified version of the unified theory of acceptance and use of technology (UTAUT) to evaluate disposition and satisfaction with computerised decision support systems (CDSS)	Quantitative	North America	Positively impacted the work of pharmacists	Organisational structures that facilitate CDSS use and user satisfaction affect the extent to which pharmacy and health care management maximise use in clinical pharmacy setting
24	Fan et al. (2021) [54]	Real-world utilisation of AI health chatbot for primary care self-diagnosis	Mixed	Asia	1. Trusted to support patients care 2. Easily applicable in patient care	Although the AI tool is perceived convenient in improving patient-care, issues and barriers exist
25	Fritsch et al. (2022) [55]	Perception about artificial intelligence in healthcare	Quantitative	Europe	1. Accurate diagnosis 2. Improved patient outcomes 3. Promotes personal care	Patients and their companions are open to AI usage in healthcare and see it as a positive development
26	Garzon-Chavez et al. (2021) [56]	Utilisation of AI-assisted computed tomography screening tool for COVID-19 patient at triage	Quantitative	South America	1. Facilitates diagnostic decisions by clinicians 2. Facilitates workflow 3. Compatible with existing technology	There were differences in laboratory parameters between cases at the intensive care and non-intensive care units
27	Goldman et al. (2021) [57]	Model based on Artificial Intelligence Neural Network (ANN) for predicting Coronary Heart Diseases risk	Quantitative	Asia	1. Accurate diagnosis 2. Facilitates referral decisions	The artificial intelligence neural network model is a promising approach for predicting coronary heart disease-risk and a good screening procedure to identify high-risk subjects

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
28	Golpour et al. (2020) [58]	Compare support vector machine, naïve Bayes and logistic regressions to determine the diagnostic factors that can predict the need for Coronary Angiography	Quantitative	Asia	1. Cost effective 2. Accurate and improved diagnosis 3. Supports workflow	Gender, age and fasting blood sugar found to be the most important factors that predict the result of coronary angiography
29	Gonçalves (2020) [59]	Nurses' experiences with technological tools to support the early detection of sepsis	Qualitative	South America	1. Early diagnosis 2. Reduced waiting time.	Nurses in the technology incorporation process enable a rapid decision-making in the identification of sepsis
30	Gonzalez-Briceno (2020) [60]	Diabetes retinopathy screening programme based on artificial intelligence	Quantitative	North America	1. Prompt and early detection of disease 2. Improved patient waiting time 3. Improved referral systems	Implementation of diabetes retinopathy screening programme in primary care promotes the early detection and prompt treatment of patients
31	Grau et al. (2019) [61]	Using Electronic Support Tools and Orders for Prevention of Smoking (E-STOPS)	Qualitative	North America	Provide essential information for physician use	Improvements in provider training and feedback as well as the timing and content of the electronic tools may increase their use by physicians
32	Hand et al. (2018) [62]	Fertility preservation discussions with pediatric and adolescent cancer patients	Quantitative	Australia	Improved adherence to clinical pathways, policy, and standards of care	The Clinical Decision Support System (CDSS) provided significant perceived benefits to oncofertility care
33	Horsfall et al. (2021) [63]	Attitudes of surgeons and the wider surgical team toward the role of artificial intelligence in neurosurgery	Mixed	North America	Very useful in facilitating and predicting potential complications during surgery	Artificial intelligence widely accepted as a useful tool in neurosurgery
34	Hsiao et al. (2013) [64]	Factors affecting acceptance of Pain Management Decision Support System (PM-DSS) by nurse anaesthetists	Quantitative	Asia	Promotes the work of nurse anaesthetists	Findings would help hospital managers understand the important considerations for nurse anaesthetists in accepting PM-DSS
35	Hu et al. (2019) [65]	Using Rough Set Theory (RST) and Dempster-Shafer Theory (DST) of evidence to remedy Major Adverse Cardiac Event (MACE) prediction	Quantitative	Asia	High diagnostic potential	The model achieved better performance for the problem of MACE prediction when compared with the single models
36	Huang et al. (2017) [66]	Data-mining based approach for Major Adverse Cardiac Events (MACE) prediction	Quantitative	Asia	High potential for accurate diagnosis	The proposed iterative boosting approach has demonstrated great potential to meet the challenge of MACE prediction for acute coronary syndrome (ACS) patients
37	Huang et al. (2021) [67]	Using magneticocardiography parameters to detect Coronary Artery Diseases in patients with chest pain	Quantitative	Asia	1. Potential for accurate diagnosis 2. Could save patients time	The method of multilayer perceptron neural network, magnetcocardigraphy is applicable in identifying coronary artery disease in patients with chest pain, which is beneficial for detection of coronary artery disease

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
38	Isbanner et al. (2022) [68]	Public judgments about AI use in healthcare	Quantitative	Australia	1. Enhanced speed of service 2. Improved patient outcomes 3. Accurate diagnosis	AI systems should augment rather than replace humans in the provision of healthcare
39	Jauk et al. (2021) [69]	Machine learning-based application for predicting the risk of delirium for in-patients	Mixed	Europe	1. Accurate in predicting patient conditions 2. Improved workflow	In order to improve quality and safety in healthcare, computerised decision support should predict actionable events and be highly accepted by users
40	Joloudari et al. (2020) [70]	Integrated method using random trees (RTs), decision tree of C5.0, support vector machine (SVM), and decision tree of Chi-squared automatic interaction detection (CHAID)	Quantitative	Asia	High potential for accurate diagnosis	The random tree model yielded the highest accuracy rate than others
41	Jones et al. (2022) [71]	Comprehensive Clinical Decision Support (CDS) to predict end-user acceptance of Thoracic Trauma CDS systems care	Qualitative	North America	1. Reduced medical errors 2. Comprehensive care 3. Reduced patient waiting time	End-user feedback reinforces intention towards factors that improve the acceptance and use of a CDS map for patients with thoracic trauma
42	Kanagasundaram et al. (2016) [72]	Using in-patient Acute Kidney Injury (AKI) Computerised Clinical Decision Support (CCDS)	Qualitative	Australia	Potentially useful prompt to early clinical re-assessment	Systems intruding on workflow, particularly involving complex interactions, may be unsustainable even if there has been a positive impact on care
43	Kayvanpour et al. (2021) [73]	Genome-wide miRNA levels in a prospective cohort of patients with clinically suspected Acute Coronary Syndromes by applying an in Silico Neural Network	Quantitative	Europe	1. High potential for accurate diagnosis 2. Saves patient time 3. Improved workflow	The approach opens the possibility to include multi-modal data points to further increase precision and performance classification of other differential diagnoses
44	Kim et al. (2017) [74]	Neural Network (NN) based prediction of Coronary Heart Disease risk using feature correlation analysis (NN-FCA)	Quantitative	Asia	High potential for accurate and timely diagnosis	The model was better than Framingham risk score (FRS) in terms of coronary heart diseases risk prediction
45	Kisling et al. (2019) [75]	Automatic treatment planning system for conventional radiotherapy of Cervical Cancer	Quantitative	Africa	1. Facilitates diagnostics decisions by clinicians 2. Promotes workflow	Fully automatic treatment planning is effective for cervical cancer radiotherapy and may provide a reliable option for low-resource clinics
46	Krittanawong et al. (2021) [76]	Deep neural network to predict in-hospital mortality in patients with Spontaneous Coronary Artery Dissection (SCAD)	Quantitative	North America	High potential for diagnostic accuracy	The deep neural network model was associated with higher predictive accuracy and discriminative power than logistic regression or ML models for identification of patients with ACS due to SCAD prone to early mortality
47	Lee (2015) [77]	Emergency department decision support system that couples machine learning, simulation, and optimisation to address improvement goals	Mixed	North America	1. Reduced EM re-admissions 2. Reduced cost of care 3. Reduced patient length of stay 4. Improved patient data	General improvement in patient care at the emergency care department

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
48	Liberati et al. (2017) [78]	Barriers and facilitators to the uptake of an evidence-based Computerised Decision Support Systems (CDSS)	Qualitative	Europe	Fosters organisational learning and improves practitioner skills	Attitudes of healthcare workers towards scientific evidence and guidelines, quality of inter-disciplinary relationships, and organisational ethos of transparency and accountability need to be considered when exploring facility readiness to implement AI tools
49	Li et al. (2021) [79]	Machine learning-aided risk stratification system to simplify the procedure of the diagnosis of Coronary Artery Disease	Quantitative	Asia	1. Helps improve diagnostic accuracy 2. Reduces patient waiting time	The model could be useful in risk stratification of prediction for the coronary artery disease
50	Liu et al. (2021) [80]	Machine learning models for predicting mortality in Coronary Artery Disease (CAD) patients with Atrial Fibrillation (AF)	Quantitative	Asia	1. Potential for improved and accurate diagnosis 2. Improve patient turnaround time	Combining the performance of all aspects of the models, the regularisation logistic regression model was recommended to be used in clinical practice
51	Love et al. (2018) [81]	Using AI-based Computer-Assisted Diagnosis (CADx) in training healthcare workers	Quantitative	North America	1. Facilitates diagnostics decisions by clinicians 2. Promotes workflow	A portable ultrasound system with CADx software can be successfully used by first-level healthcare workers to triage palpable breast lumps
52	MacPherson et al. (2021) [82]	Costs and yield from systematic HIV-TB screening, including computer-aided digital chest X-Ray	Quantitative	Africa	1. Facilitates diagnostics decisions by clinicians 2. Reduced patient waiting time 3. Improved patient health outcomes	Digital chest X-Ray computer-aided digital with universal HIV screening significantly increased the timelines and completeness of HIV and TB diagnosis
53	McCoy (2017) [83]	Machine learning-based sepsis prediction algorithm to identify patients with sepsis earlier	Quantitative	North America	1. Improved patient outcomes 2. Reduction in mortality rate	The machine learning-based sepsis prediction algorithm improved patient outcomes
54	Mehta et al. (2021) [84]	Knowledge, perceptions, and preferences about AI use in medical education	Quantitative	North America	1. Improved clinical and administrative functions 2. Provide useful preventive health suggestions to patients 3. Accurate diagnosis 4. Improve referral procedures	Optimistic about AI's capabilities to carry out a variety of healthcare functions, including clinical and administrative Sceptical about AI utility in personal counselling and empathetic care
55	Moon (2018) [85]	Automated delirium-risk assessment system (Auto-DelRAS) that automatically alerts healthcare providers of an intensive care unit patient's delirium-risk	Quantitative	Asia	1. Improved data 2. Improved patient outcome 3. Quality diagnostic ability	A relatively high level of predictive validity was maintained with the Auto-DelRAS system, even one year following clinical application

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
56	Morgenstern et al. (2021) [86]	Impacts of artificial intelligence (AI) on public health practice	Qualitative	North America & Asia	Improved diagnosis and disease surveillance	Experts are cautiously optimistic AI's potential to improve diagnosis and disease surveillance. However, perceived substantial barriers like inadequate regulation exist
57	Motwani et al. (2017) [87]	Traditional prognostic risk assessment in patients undergoing non-invasive imaging	Quantitative	North America	1. Potential for accurate diagnostic capacity 2. Improved turnaround time	Machine learning combining clinical and coronary computed tomographic angiography data was found to predict 5-year all-cause mortality significantly better than existing models
58	Betriana et al. (2021a) [88]	Access to palliative care (PC) by integrating predictive model into a comprehensive clinical framework	Quantitative	North America	1. Improved workflow 2. Improved patient outcomes	A machine learning model can effectively predict the need for in-patient palliative care consult and has been successfully integrated into practice to refer new patients to palliative care
59	Naushad et al. (2018) [89]	Coronary artery disease risk and percentage stenosis prediction models using ensemble machine learning algorithms, multifactor dimensionality reduction and recursive partitioning	Quantitative	Asia	1. High potential for diagnostic accuracy 2. Timely diagnosis	The model exhibited higher predictability both in terms of disease prediction and stenosis prediction
60	Nydert et al. (2017) [90]	Clinical Decision Support System (CDSS) among paediatricians	Qualitative	Europe	Very useful during emergency care	Generally, the system is considered very useful to patient drug management
61	O'Leary et al. (2014) [91]	Support systems in healthcare and the concept of decision support for clinical pathways	Mixed	Europe	1. Reduced medical error 2. Allows for multi-disciplinary intervention	The success of these systems depend on other factors outside of itself
62	Orlenko et al. (2020) [92]	Tree-based Pipeline Optimisation Tool (TPOT) to predict angiographic diagnoses of Coronary Artery Disease (CAD)	Quantitative	Europe	High potential for accurate diagnosis	Phenotypic profile that distinguishes non-obstructive coronary artery disease patients from non-coronary artery disease patients is associated with higher precision
63	Pattarabanjird et al. (2020) [93]	Novel machine learning that combine traditional Cardiac Risk Factors (CRF) with a Single Nucleotide Polymorphism (SNP) in a gene associated with human Coronary Artery Disease severity	Quantitative	North America	1. Could improve diagnostic accuracy 2. Improved workflow	The model improved prediction of coronary artery disease severity
64	Pieszko (2019) [94]	Risk assessment tool based on easily obtained features, including haematological indices and inflammation markers	Quantitative	Europe	1. High diagnostic capacity 2. Improved patient outcomes	The machine-learning model can provide long-term predictions of accuracy comparable or superior to well-validated risk scores

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
65	Ploug et al. (2021) [95]	Preferences for the performance and explainability of AI decision making in health care	Quantitative	Europe	1. Improved diagnosis and treatment 2. Improved patient outcomes	Physicians must take ultimately responsibility for diagnostics and treatment planning, AI decision support should be explainable, and AI system must be tested for discrimination
66	Polero (2020) [96]	Random forest and elastic net algorithms to improve acute coronary syndrome risk prediction tools	Quantitative	South America	1. High potential for accurate diagnosis 2. Improved turnaround time	Random forest significantly outperformed exiting models and can perform at par with previously developed scoring metrics
67	Prakash and Das (2020) [97]	Factors influencing the uptake and use of intelligent conversational agents in mental healthcare	Qualitative	Asia	1. Improved quality of care 2. Reduced patient waiting time	AI tools have proven efficacious in improving the health outcomes of patients. However, there are inadequate legal regimes to guide usage
68	Pumplun et al. (2021) [98]	Factors that influence the adoption of machine learning systems for medical diagnosis in clinics	Qualitative	Europe	Accurate diagnosis	Many clinics still face major problems in the application of machine learning systems for medical diagnostics
69	Richardson et al. (2021) [99]	Patient views of diverse applications of AI in healthcare	Qualitative	North America	1. Improved patient outcomes 2. Wider range of conditions 3. Accurate diagnosis	Addressing patient concerns relating to AI applications in healthcare is essential for effective clinical implementation
70	Romero-Brufau (2020) [100]	Reduce unplanned hospital readmissions through the use of artificial intelligence-based clinical decision support	Quantitative	North America	1. Reduced readmission rates 2. Improved patient outcome	Six months following a successful application of intervention, readmissions rates decreased by 25%
71	Sarwar et al. (2019) [101]	Perspectives on AI implementation in clinical practice	Quantitative	North America & Europe	1. Facilitates and improves service delivery 2. Accurate diagnosis 3. Improve traditional practice 4. Improve diagnostic capacity	Most respondents envision eventual rollout of AI-tools to complement and not replace physicians in healthcare
72	Scheetz et al. (2021) [102]	Diagnostic performance, feasibility, and end-user experiences of AI assisted diabetic retinopathy	Mixed	Australia	1. Real-time reports 2. Accurate diagnoses	AI in healthcare well-accepted by patients and clinicians
73	Schuh (2018) [103]	Creation and modification of Arden-Syntax-based Clinical Decision Support Systems (CDSSs)	Quantitative	Australia	1. Improved data quality 2. Reduced cost of care	Despite its high utility in patient care, inconsistent electronic data, lack of social acceptance among healthcare personnel, and weak legislative issues remain
74	Sendak (2020) [104]	Integration of a deep learning sepsis detection and management platform, sepsis watch, into routine clinical care	Quantitative	North America	1. Early detection of sepsis 2. Improved workflow	Although there is no playbook for integrating deep learning into clinical care, learning from the sepsis watch integration can inform efforts to develop machines learning technologies at other healthcare delivery systems

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
75	Sherazi et al. (2020) [105]	Propose a machine learning-based on 1-year mortality prediction model after discharge in clinical patients with acute coronary syndrome	Quantitative	Asia	1. Produced accurate diagnosis 2. Reduced delays in diagnosis	The model would be beneficial for prediction and early detection of major adverse cardiovascular events in acute coronary syndrome patients
76	Sujan et al. (2022) [106]	Views about AI in healthcare	Qualitative	Europe	1. Diagnostic precision 2. Faster services	Safety and assurance of healthcare AI need to be based on a systems approach that expands the current technology-centric focus
77	Tayefi et al. (2017) [107]	Establish a predictive model for coronary heart disease using a decision tree algorithm	Quantitative	Asia	May support accurate and timely diagnosis	Proven to be accurate, specific and sensitive model for identifying the presence of coronary heart disease
78	Terry et al. (2022) [108]	Views about the use of AI tools in healthcare	Qualitative	North America	Improved healthcare	Use of AI in primary healthcare may have a positive impact, but many factors need to be considered regarding its implementation
79	Tscholl et al. (2018) [109]	Perceptions about patient monitoring technology (visual patient) for transforming numerical and waveform data into a virtual model	Mixed	Europe	1. Improved turnaround time 2. Easy to use 3. Effective in non-monitoring care	The new avatar-based technology improves the turnaround time in patient care
80	Uzir et al. (2021) [110]	AI-enabled smartwatch use in healthcare	Quantitative	Asia	1. Significantly reduce large patient attendance 2. Reduced cost and inconvenience of access to essential healthcare 3. Promotes efficient healthcare 4. Very useful during national emergencies 5. Automation of critical health services 6. Promotes personnel care	AI promoting health democracy and personal healthcare
81	van der Heijden (2018) [111]	Incorporation of IDx-diabetes retinopathy (IDx-DR 2.0) in clinical workflow, to detect retinopathy in persons with type 2 diabetes	Quantitative	Europe	1. Improved data 2. Improved patient outcome 3. Quality diagnostic ability	High predictive validity recorded for IDx-DR 2.0 device
82	van der Zander et al. (2022) [112]	Perspectives about AI use in healthcare	Quantitative	Europe	1. Improved quality of care 2. Speed of service 3. Accurate diagnostics	Both patients and physicians hold positive perspectives towards AI in healthcare

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
83	Velusamy et al. (2021) [113]	Machine learning algorithm to accurately diagnose coronary artery disease	Qualitative	Asia	1. High potential for accurate diagnosis 2. Can improve patient turnaround time	Weighted-average voting algorithm good in reliably discriminating the coronary artery disease patients from healthy ones with high precision, and therefore it can be used for developing a decision support system for diagnosing coronary artery disease at an early stage
84	Visram et al. (2023) [114]	Attitudes towards AI and its future applications in medicine and healthcare	Qualitative	Europe	1. Improved health outcomes 2. Accurate diagnosis	Children and young people to be included in developing AI. This requires an enabling environment for human-centred AI involving children and young people
85	Walter et al. (2020) [115]	Automatic pain recognition (APR) system for the recognition of pain quality	Quantitative	Europe	1. Accurate in detecting pain 2. Helps detect and avoid over or under-supply of analgesics in patients	Automated pain recognition system is useful in managing pain during patient care
86	Wang et al. (2021a) [116]	AI-powered clinical decision support systems in clinical decision-making scenarios	Qualitative	Asia	1. Facilitates diagnostics decisions by clinicians 2. Promotes workflow 3. Improved diagnosis and treatment 4. Improved turnaround time	Despite difficulties, there is a strong and positive expectation about the role of AI- clinical decision support systems in the future
87	Wang et al. (2021b) [117]	Utilisation of social support chatbot for online health community	Mixed	Asia	1. Improved diagnostic and treatment time 2. Improved patient health outcomes	Chatbot architecture social support has proven useful in supporting individual members who seek emotional support
88	Wittal et al. (2022) [118]	Public perception and knowledge of AI use in healthcare, therapy, and diagnosis	Quantitative	Europe	1. Rapid and accurate diagnoses 2. Longer and better quality of life	Need to improve education and perception of medical AI applications by increasing awareness, highlighting the potentials, and ensuring compliance with guidelines and regulations to handle data protection
89	Xu (2020) [119]	Medical-grade wireless monitoring system based on wearable and artificial intelligence technology	Quantitative	Asia	1. Improved workflow 2. Fast and better diagnosis	The AI tool can provide reliable psychological monitoring for patients in general wards and has the potential to generate more personalised pathophysiological information related to disease diagnosis and treatment
90	Yurdaisik and Aksoy (2021) [120]	Knowledge and attitudes of workers at radiology department towards AI applications	Quantitative	Europe & Asia	1. Saves time 2. Improves workflow	AI applications are very helpful in improving the health outcome of patients

Table 2 (continued)

Ser	Author(s)	Purpose/ Objective	Approach	Continent	Opportunities	Conclusions
91	Zhai et al. (2021) [121]	Develop and test a model for investigating the factors that drive radiation oncologists' acceptance of AI contouring technology	Quantitative	Asia	Improved workflow and patient outcome	Clinicians had very high perceptions about AI-assisted technology for radiation contouring
92	Zhang et al. (2020) [122]	Provide Optimal Detection Models for suspected Coronary Artery Disease detection	Quantitative	Asia	1. Promote accurate diagnosis 2. Improve turnaround time	Multi-modal features fusion and hybrid features selection can obtain more effective information for coronary artery disease detection and provide a reference for physicians to diagnosis coronary artery disease patients
93	Zheng et al. (2021) [123]	Clinicians' and other professional technicians' familiarity with, attitudes towards, and concerns about AI in ophthalmology	Quantitative	Asia	Improved health outcomes for patients	AI tools are relevant in ophthalmology and would help improve patient health outcomes
94	Zhou et al. (2019) [124]	Examine concordance between the treatment recommendation proposed by Watson for Oncology and actual clinical decisions by oncologists in a cancer centre	Quantitative	Asia	1. Facilitates diagnostics decisions by clinicians 2. Improved diagnostic tests	There is concordance between AI tools and human clinician decisions
95	Zhou et al. (2020) [125]	Develop and internally validate a Laboratory-Based Model with data from a Chinese cohort of inpatients with suspected Stable Chest Pain	Quantitative	Asia	1. Improved diagnostic potential 2. Improved turnaround time	The present model provided a large net benefit compared with coronary artery diseases consortium ½ score (CAD1/2), Duke clinical score, and Forrester score

in this review. The included 95 articles were distributed across the following years: 2023 = 1(1%), 2022 = 7(7%), 2021 = 30(32%), 2020 = 23(24%), 2019 = 11(12%), 2018 = 9(9.5%), 2017 = 9(9.5%), 2016 = 1(1%), 2015 = 2(2%), 2014 = 1(1%), and 2013 = 1(1%) (See Fig. 2). Additionally, 65(68%) of the reviewed articles adopted the quantitative approach, 20(21%) applied the qualitative, and 10(11%) used the mixed method approach. Furthermore, the reviewed articles are conducted across: Asia = 36(39%), North America = 25(26%), Europe = 19(20%), Australia = 5(5%), South America = 4(4%), Africa = 3(3%), North America & Asia = 1(1%), North America & Europe = 1(1%), and Europe & Asia = 1(1%) (See Fig. 3). Clearly, the articles reviewed were disproportionately concentrated in three continents (Asia, North America, and Europe), accounting for over one-third of the total articles reviewed. Though Australia, South America, and Africa recorded very few articles in this review, this may mean that most of the articles from these continents did not meet our inclusion standards.

Improvement in patient diagnosis

The majority of the articles, 66 (69%) reviewed [31, 32, 35, 37–39, 41, 43, 44, 47, 49–52, 55–58, 62, 63, 65–70, 73–76, 79–82, 84–87, 89, 92, 94–99, 101–107, 110–112, 114–119, 122–125], reported a high sensitivity of AI applications in detecting various clinical conditions. It is widely reported [44, 50, 58, 62, 63, 65–67, 92, 110, 115] that AI applications would significantly improve the accuracy of clinical diagnosis. While these intelligent machines could act independently during patient-care [32, 37, 43, 98, 101], they may also enhance the quality of decisions reached by clinicians [49–52, 55–58, 69, 103, 119]. According to van der Zander et al. [112], Visram et al. [114], and Wittal et al. [118], given that AI tools thrive on large datasets, they are better at diagnosing (Artificial Clinicians) far more diseases in a relatively shorter time than human clinicians. This looks very promising, considering the ability of AI tools to leverage algorithms that help to predict accurately future outbreaks of diseases within specific

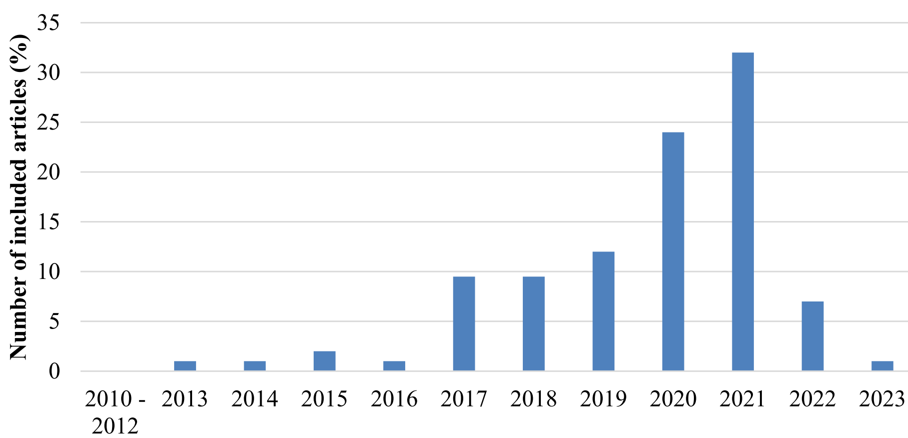

Fig. 2 Yearly distribution of included articles in percentages

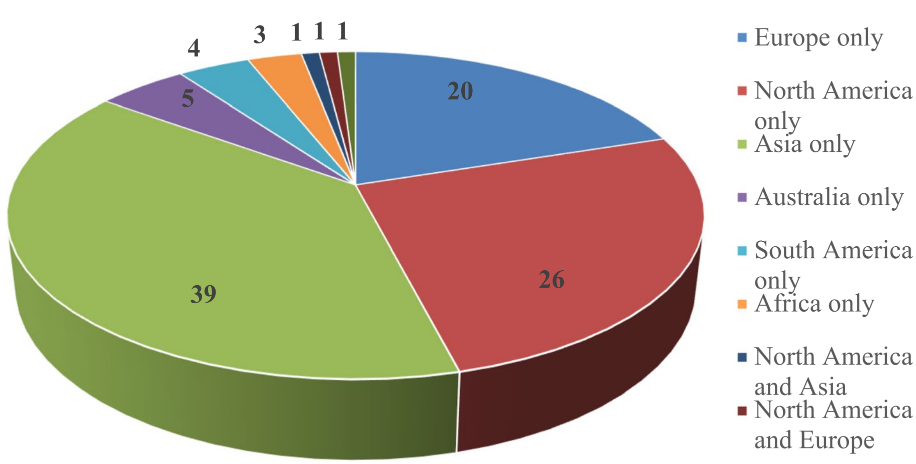

Fig. 3 Geographical distribution of included articles in percentages

populations [58, 62, 63, 65, 74, 81, 119]. Although there are concerns about the ability of AI tools to act independently, the public is cautiously optimistic that these “artificial clinicians” could still be controlled to act responsibly [66, 73, 76, 84, 89] to reduce errors.

Reduction of medical errors and improvement in workflow

Evidence (50; 53%) suggests that as AI tools are increasingly introduced into the workflow, the incidence of medical errors associated with workload and stress will significantly reduce [32, 34, 42–44, 47–49, 52–55, 57, 58, 61–64, 67, 68, 70, 71, 73, 74, 77, 79–83, 86, 88, 91, 93, 98, 100, 101, 104, 105, 109–112, 115, 116, 118–122, 124]. Meanwhile, the global healthcare system is seeing a rapid reduction in the workforce per unit population while the number of patients seeking care is ever-increasing [105, 110, 124]. This situation arguably contributes to increases in the incidence of medical errors (sometimes fatal) [55, 101]. However, if properly deployed, AI tools can offer superior care and significantly reduce these errors [55, 67, 104, 110, 116]. This is significant because patients can be assured of adequate protection from avoidable medical errors. Consistent with Catho et al. [45], several other articles [52, 55, 57, 58, 62, 63, 67, 68, 110, 122] found that AI applications could easily be integrated into the workflow and actually facilitate clinical decisions by physicians and produce near-accurate data.

Accurate and reliable data

Healthcare decisions, especially those regarding patients’ diagnoses, rely heavily on data that are incontrovertible, accurate, and reliable [48, 77, 87, 89, 91, 92, 95–99, 101–107]. Therefore, it is incumbent on healthcare managers to develop health information management systems that guarantee an uninterrupted supply of accurate and reliable patient data in real time for both administrative and clinical decision-making [79, 82, 89, 91, 93, 104]. Many of the reviewed articles (39; 41%) [34, 35, 48, 77–82, 84, 85, 87, 89, 91–93, 95–99, 101–107, 111–114, 116–119, 122, 124, 125] reported that AI tools hold enormous potential to process large volumes of patients’ data and make timely and accurate inferences. Apart from providing rich and accurate data for decision-making in clinical settings, AI tools provide expeditious and reliable data for quick action in epidemiological and public health fields [80, 89, 112]. Although concerns have been raised about data privacy [84, 94, 104, 113], the public believes that AI tools would positively impact healthcare decisions and enhance trustworthiness to improve patient care.

Improvement in patient-care

Artificial intelligent tools are credited for their ability to mitigate, if not eliminate, most of the factors that currently predict poor patient outcomes (23; 24%) [32, 33, 36, 40, 45, 49, 54, 55, 60, 71, 82, 94–96, 100, 103, 108, 109, 113, 117, 121, 123, 125]. These include errors in clinical diagnosis, long waiting times, poor staff attitudes, inaccurate and missing patient data, workload and staff burnout, and discrimination because a large number of patients need care [32, 40, 49, 55, 82, 109, 121]. According to Fritsch et al. [55], Wang et al. [117], MacPherson et al. [82], and Ploug et al. [95], when AI tools that serve as machine clinicians are applied in combination with human clinicians, a rich and valuable context is provided to improve the quality of care provided to patients. Moreover, AI tools provide valuable opportunities for patients to receive needed care remotely [54, 96, 121, 123]. For instance, domestic caregivers could receive valuable guidance from machine clinician AI tools when confronted with difficult decisions regarding patients with chronic conditions such as cerebrovascular accident and related conditions, hypertension, and diabetes. This reduces the stressors associated with caring for patients with such chronic conditions and improves the needed quality of care [82, 95, 103], which may prevent or reduce medical emergencies.

Prompt detection of medical emergencies

Changes in the conditions of patients can sometimes be sudden and unpredictable, especially during emergency care [37, 51, 60, 106, 110]. As reported in 16(17%) of the selected articles [31, 33, 35–37, 46, 51, 59, 60, 72, 90, 102, 106, 109, 110, 113], with the introduction of AI tools into healthcare, clinicians can now detect early and act swiftly in providing life-saving care to patients during medical emergencies. These are possible because AI tools have features that could trigger instantaneous alerts on imminent changes in patient conditions, such as seizures and strokes, and ensure timely medical interventions [31, 36, 51, 59, 107]. The public [51, 72, 110, 113] is hopeful that if well implemented, AI tools could become valuable in the management of medical emergencies.

Discussion

The utilisation of AI tools in governance, academia, manufacturing, security, entertainment, space and marine exploration, health, etcetera, is gaining popularity among researchers globally [15, 24]. There are several studies about the utility of AI tools in other fields [10, 15, 24], yet few studies exist on direct AI applications in patient care [13]. Moreover, most of the studies that examined the application of AI tools in health were not conducted in the area of patient care [2, 13]. Affirming this, the current study found that out of 527 articles on AI use in health, only 95(31%) met the inclusion standards and formed part of this review. Besides, consistent with Khalid et al. [13] and Naik et al. [24], the current study reports that the articles reviewed were disproportionately concentrated in three continents (Asia, North America, and Europe), which account for over one-third of the total articles reviewed. We discuss our findings under the following themes: improvement in patient diagnosis, reduction in medical errors and facilitation of workflow, accurate and reliable data, improvement in patient care, and prompt detection of medical emergencies.

Improvement in patient diagnosis

Accurate and timely determination of a patient's diagnosis defines the patient-clinician relationship, which becomes a key prerequisite for administering treatment for improved patient outcomes [13, 130]. Center of Intellectual Property and Technology Law [12] explained that it is both a legal and moral obligation for a clinician to exercise due diligence in diagnosing patients' conditions and disclosing the same to the patient. The suggestion is that the design of AI tools provides a superior advantage of delivering accurate diagnoses in real time [14, 19]. Consistent with this, our review found that these machine clinician AI tools could significantly improve the accuracy of clinical diagnosis. Moreover, integrating AI tools into the care process will provide a robust and trustworthy context for clinicians to shape and improve their own diagnostic decisions. For instance, Al-Zaiti et al. [35] reported that an AI model outperformed both commercial interpretation software and experienced clinician interpretation in diagnosing underlying Acute Myocardial Ischemia in patients with chest pain. Again, Amarbayasgalan et al. [37] reported that the Reconstructive Error (RE) based Deep Neural Networks (DNNs) AI model outperformed other models in diagnosing coronary heart disease risk. Also, Ayatollahi et al. [38] found that Artificial Intelligence Neural Network (ANN) and Support Vector Machine (SVM) algorithms had higher sensitivity in diagnosing Cardiovascular Disease.

The caution, however, is that the current review disaffirms previous studies [10, 11] that reported the possibility of AI tools committing serious errors in their diagnostic decisions based on factors like inaccurate and biased data and inadequate machine training and learning. This notwithstanding, the findings of the current review based on a large body of previous studies [12–14, 19, 130] suggest that AI tools in patient care significantly address shortcomings in the traditional diagnostic regime. Thus, if well implemented, AI tools in patient care could stimulate and accelerate the realisation of SDG 3.4, which calls for a decrease by one-third the avoidable deaths from non-communicable diseases by the year 2030 [3, 7].

Reduction in medical errors and workflow

There is a correlation between increased workload, stress, and burnout of clinicians and the occurrence of medical errors in patient care [9–11]. Some of these medical errors result in serious negative health outcomes (including death) of patients. Our review found that AI tools can help minimise the incidence of medical errors associated with hospital-based stressors. In one example, Catho et al. [45] found that Computerised Decision Support Systems (CDSSs) model could actually reduce medical errors and support the clinical decisions of physicians. Another finding [51] suggests that the Coronary Heart Disease (CHD) prediction AI model could reduce medical errors and shape the clinical decisions of physicians. Thus, IA tools can enhance the trust that patients have for healthcare professionals. Additionally, the reviewed studies [5, 11, 15, 131] reported that AI tools will serve the best interest of patients. This may mean that these machine clinician AI tools seem to provide a great way forward in healthcare presently.

Accurate and reliable data

The role of robust, accurate, and reliable data in the decision-making process regarding patient care cannot be overemphasised [13, 15]. Several studies [11, 14, 35, 80] recognised the super-abilities of AI tools in procuring, organising, and preserving large volumes of datasets for use in both clinical and administrative decisions concerning patient care. For example, Huang et al. [67] reported that the Major Adverse Cardiac Events (MACE) prediction AI model can leverage a large data-mining-based approach in predicting acute coronary syndrome (ACS) in patients. Again, Kayvanpour et al. [73] reported that the Silico Neural Network AI model can utilise multimodal data points in accurately predicting Acute Coronary Syndromes in patients. However, the findings from the current study oppose some earlier ones [10, 12], suggesting that AI tools could seriously compromise data privacy. In addition, AI tools are vulnerable to attack by computer hackers who could misuse patient records [9, 19]. Although these concerns are legitimate, some previous studies [2, 15] suggest that AI tools have inherent security mechanisms against data leaks and theft. Moreover, in the long term, the odds are high that AI tools will guarantee more reliable, accurate, and timely data in patient care. Thus, with proper design and implementation, including an effective ethicolegal framework, AI tools used in patient care would help in achieving SGD 3.b, which calls for research and development of vaccines and medicines for communicable and non-communicable diseases by 2030 [3, 7].

Improvement in patient-care

The traditional patient-care regime is largely characterised by delays in receiving care, discrimination, poor care-provider attitude, staff fatigue and stress, inadequate staff, misdiagnosis, treatment-diagnosis mismatches, under- and over-prescription, missing patient records, etcetera [8, 15]. These factors contribute to the ever-increasing incidence of mortality and complications in patient conditions recorded in most healthcare facilities worldwide [14]. However, our review found that AI tools have the capacity to significantly reduce, if not eliminate, most of the factors that currently undermine patent care. For example, Pattarabanjird et al. [93] reported a general improvement in the health of patients with severe Coronary Artery Disease when the Single Nucleotide Polymorphism (SNP) AI model was applied. Also, Uzir et al. [110] reported that AI-enabled smartwatch applications are promoting health democracy and personal healthcare. Meanwhile, Walter et al. [115] found that the Automatic pain recognition (APR) AI system had a high sensitivity to pain in patients, which helps in pain management.

AI tools have more effective and efficient data storage and protection ability, data interpretation ability, accurate diagnostic ability, and exceptionally expeditious and reliable service to patients [8, 11, 14]. For instance, previous studies [7, 13], as corroborated by the findings from our current review, indicated that AI tools have the ability to provide needed care remotely to patients who may not necessarily be present physically at the hospital. This will help reduce large patient numbers at the hospital and improve the overall turnaround time for care. However, our review contradicts other previous studies [20, 132], which raised concerns over AI tools providing care in a discriminatory manner. Thus, such findings question the utility of AI tools in mental health services and are sceptical about their ability to provide non-pharmacological care. Regardless, a large body of previous studies [7, 13–15] suggests that AI tools could significantly improve the total quality of care to patients. Ultimately, AI tools would contribute significantly to the realisation of the universal health coverage provided in SDG 3.8.

Prompt detection of medical emergencies

Critically ill patients are constantly under close monitoring for even the slightest change in condition [15, 130]. So far, AI tools have proven very helpful in saving the lives of many patients [11, 131]. For instance, with the introduction of AI tools into healthcare, clinicians can detect and act swiftly to provide life-saving care to patients during medical emergencies [5, 15]. One evidence is that the Automated Delirium-Risk Assessment System (Auto-DelRAS) has a high level of validity in predicting delirium risk in patients in the intensive care unit [85]. Also, Hu et al. [65] reported that the Rough Set Theory (RST) and Dempster-Shafer Theory (DST) have higher sensitivity in predicting the incidence of Major Adverse Cardiac events during medical emergencies. Further evidence [76] suggests that deep neural network AI application has a better sensitivity in predicting mortality among patients with Spontaneous Coronary Artery Dissection (SCAD). Thus, given its several algorithms, these intelligent applications could detect imminent changes in patient conditions and trigger instantaneous alerts for quick interventions [9]. Moreover, we reported that there are AI applications that could significantly mitigate errors associated with AI tools [9, 14, 130]. So far, there seems to be no better or more competent alternative to AI tools in the management of medical emergencies.

Strengths and limitations

The review attempts to explore evidence of the perceived positive effects of AI applications in patient care from a global perspective. To ensure reproducibility, reliability, and trustworthiness of our findings, there was strict adherence to the following: first, all authors independently searched for and screened articles using the MeSH terms. Moreover, guided by the inclusion and exclusion guidelines and a checklist, all selected full-text articles were subjected to a quality rating. Additionally, to establish validity and replicability, all authors participated in a thorough data extraction process and review.

This review also has some limitations. First, relying on only peer-reviewed articles and selecting articles written in the English language limit the literature sample used because we might have excluded other relevant articles written in other languages. Moreover, we recognise that the study may have carried weaknesses and biases contained in the reviewed articles. Therefore, the generalisability of our findings may be limited. Finally, it is important to acknowledge that regardless of the positive outcomes reported for AI tools by several randomised trials, the generalisability of the utility of these intelligent tools is yet to be established, given that the overall utility of AI tools is dependent on the quality of data and the training provided to the tools.

Recommendations for policy and research directions

We propose that governments leverage AI applications to aid and accelerate the realisation of the health-related SDGs in their jurisdictions. Specifically, governments in developing countries can provide financial support for the effective and efficient adoption of AI tools in healthcare. Secondly, there would be the need to introduce academic courses on the application of AI tools in healthcare for all categories of health professionals, especially in developing countries. Thirdly, governments in developing countries need to sponsor Biomedical Engineers to be trained in the use of AI tools in healthcare. Such training should, among other specialties, cover cyber Intelligence. In addition, public health experts and healthcare managers need to collaborate with AI developers to develop applications that can efficiently provide both pharmacological and non-pharmacological care to patients. Furthermore, we propose that AI developers need to collaborate with healthcare managers to develop AI applications that are super sensitive to socio-cultural dimensions in patient care. Lastly, we encourage WHO and other agencies to provide sponsorship for research into AI applications, patient care, and SDGs. Future research may explore how AI applications are promoting public health interventions, such as the fight against pandemics and epidemics. Also, assessing the potential negative effects of the use of AI tools in patient care is warranted.

While making these recommendations, we envisage some potential barriers. These may include non-commitment from political decision-makers to successfully implement projects incorporating AI tools into healthcare, especially in developing nations. First, budgetary constraints and increasing competing demands on governments in most developing countries may limit the implementation of these recommendations. Second, unstable power supply, cultural sensitivity and potential hesitancy to new technology, conspiracy, and prevalence of cyber Intelligence globally could undermine the smooth implementation of AI tools used in patient care in less-resourced countries.

Conclusion

AI applications are steadily and rapidly shaping the relationship between clinicians and patient care globally. This development has attracted some criticism, including potential breaches of privacy, data fraud, bias and discrimination, and decline in humanity during patient care. However, AI applications are demonstrating enhanced capacity that can change the course of our collective future for the better. Thus, AI tools have the ability to improve the accuracy of clinical diagnosis significantly and, guarantee better health outcomes for patients and mitigate, if not eliminate, most of the factors that currently predict poor patient outcomes. Furthermore, AI tools are far more efficient in generating robust and accurate data in real time and could help ease and accelerate workflow. Additionally, AI devices and applications are contributing largely to the management of medical emergencies.

Furthermore, if properly integrated into the healthcare systems and used in patient care, AI tools could accelerate the realisation of SDGs 3.4, 3.8, and 3.b. So far, there seems to be no going back on this journey of AI use, including their use as machine clinicians in patient care. Thus, the focus should be on ensuring that these tools are responsibly applied to provide the needed results—improvement in health outcomes. This study is a significant addition to existing evidence on the use of AI tools in healthcare.

Abbreviations

AI	Artificial intelligence
SDGs	Sustainable development goals
PRISMA-ScR	Preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews
MeSH	Medical subject headings

Acknowledgements

We are grateful to Lieutenant Commander (Ghana Navy) Candice FLEISCHER-DJOLETO of 37 Military Hospital, Ghana Armed Forces Medical Services, for proofreading the draft manuscript.

Authors' contributions

N.N.B., E.W.A., C.E.S., S.M., and V.K.D. Conceptualised and Designed the Review Protocols. E.W.A., V.K.D., C.E.S., F.S.A., I.S.T., L.A.A., S.M., and N.N.B. Conducted Data Collection and Acquisition. E.W.A., V.K.D., R.V.K.., C.E.S., F.S.A., I.S.T., L.A.A., S.M., and N.N.B. carried out extensive data processing and management. E.W.A., C.E.S., N.N.B., and R.V.K. developed the initial manuscript. All authors edited and considerably reviewed the manuscript, proofread for intellectual content and consented to its publication.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sector.

Availability of data and materials

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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Received: 29 November 2023 Accepted: 10 April 2024
Published online: 24 June 2024

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