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Using Artificial Intelligence In Nursing To Improve Patient Outcomes

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Abstract

The use of artificial intelligence (AI) in healthcare has the potential to greatly improve patient outcomes. In this paper, we conduct a systematic qualitative review of AI in nursing, utilizing 26 papers identified through a search on Google Scholar and selected with the PRISMA flowchart. The majority of these papers (23 out of 26) were based on a review of existing literature, while the remaining three utilized multiple methods including focus groups and interviews to understand perceptions and hesitation towards AI in patient care among different stakeholders. The papers followed a similar structure, starting with a definition of AI and describing various tools and applications in healthcare, supported by real-world examples. One common finding was the low adoption rate of AI in healthcare systems, primarily due to a lack of integration into existing patient care systems. Other challenges and ethical issues, such as the explainability of AI algorithms, were also discussed. The hesitance and resistance of stakeholders towards the use of AI was identified as a major barrier to adoption. As such, future research should focus on understanding and addressing these concerns, as well as conducting systematic studies on the integration and ethical implications of AI in nursing. Limitations of this review are also discussed.

Keywords: Artificial intelligence, nursing, patient outcomes, review.

Introduction

Artificial Intelligence (AI) has many applications in healthcare and medicine. The healthcare AI market is expected to grow from USD 14.6 billion in 2022 to USD 102.7 billion in 2028, thus registering a compounded annual growth rate of 47.6% during this period. The drivers are the generation of large and complex data sets. The constraints are the lack of AI skilled workforce. There is growing potential for AI tools in this sector. The lack of curated healthcare data is a challenge in this respect (Markets and Markets, 2022).

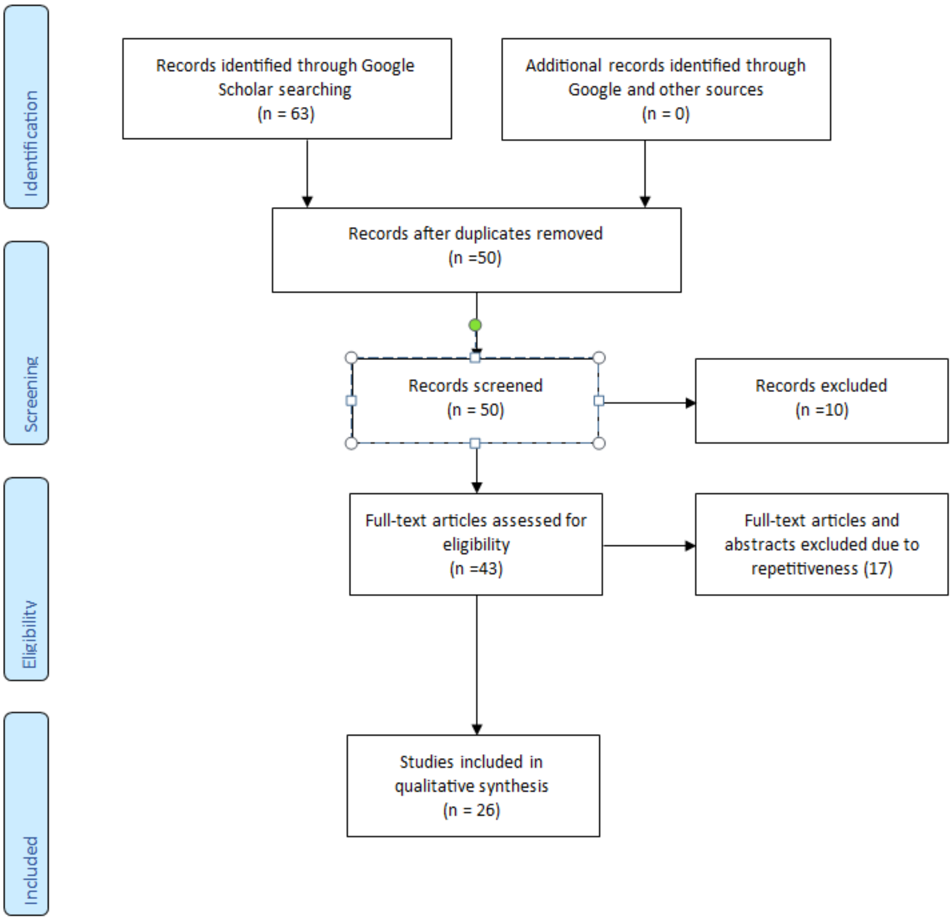
AI technologies provide prompt, economical, and better solutions for prognosis, prevention, medication, and healthcare breakthroughs. AI helps to improve the accuracy of prediction, to enhance service delivery, and to improve disease detection. AI automates the exploration and accelerated development of drugs, personalized medicine, clinical diagnosis investigations, robotic-assisted surgery, verified prescriptions, trained pregnancy care for women, radiology, and review of patient information analytics (Engineering, 2022). Currently, AI is used mostly for clinical decision-making and images. AI in healthcare and medicine benefits by better patient care, reducing medication errors, reducing costs, increasing the interactions between doctor and patient and identifying the relevant data (IBM, 2022).

Thus, AI tools are being used for many applications in healthcare and medicine. Much research has been done on AI in healthcare and medicine. This paper aims to systematically review the progress of research on AI in healthcare and medicine.

Methodology & Results

Methodology

Search terms “artificial intelligence”, “nursing”, “healthcare” and “medicine “were used in different combinations to identify the papers from Google Scholar. The identified papers were screened and selected using the PRISMA flow diagram (shown below). Finally, 26 papers were selected for this review. These papers are discussed in the sections below.



Results

A global history of AI applications in healthcare and medicine was analysed by Tran, et al. (2019) using 27,451 papers (2849 reviews) published between 1977 and 2018 retrieved from the Web of Science platform. About 84.6% were published during 2008–2018. Most applications were robotics, machine learning, Artificial Neural Networks (ANN), and Natural language Processes (NLP). They were most frequently applied in Clinical Prediction and Treatment. The highest number of papers were cancer-related, followed by Heart Diseases and Stroke, Vision impairment, Alzheimer's, and Depression. A lack of research in some high-burden areas was also noted. The need to develop national and global protocols for the adaptation of AI products for medical research was highlighted.

Three types of AI applications reviewed by Khanna (2018) were drug creation, treatment design, and medical data and records management. These applications increase access to healthcare and reduce costs to patients.

In an overview of AI in medicine, Amisha, Pathania, and Rathaur (2019) presented two diagrams of various AI applications in healthcare and their advantages and disadvantages, as given in Fig 1 and Fig 2.

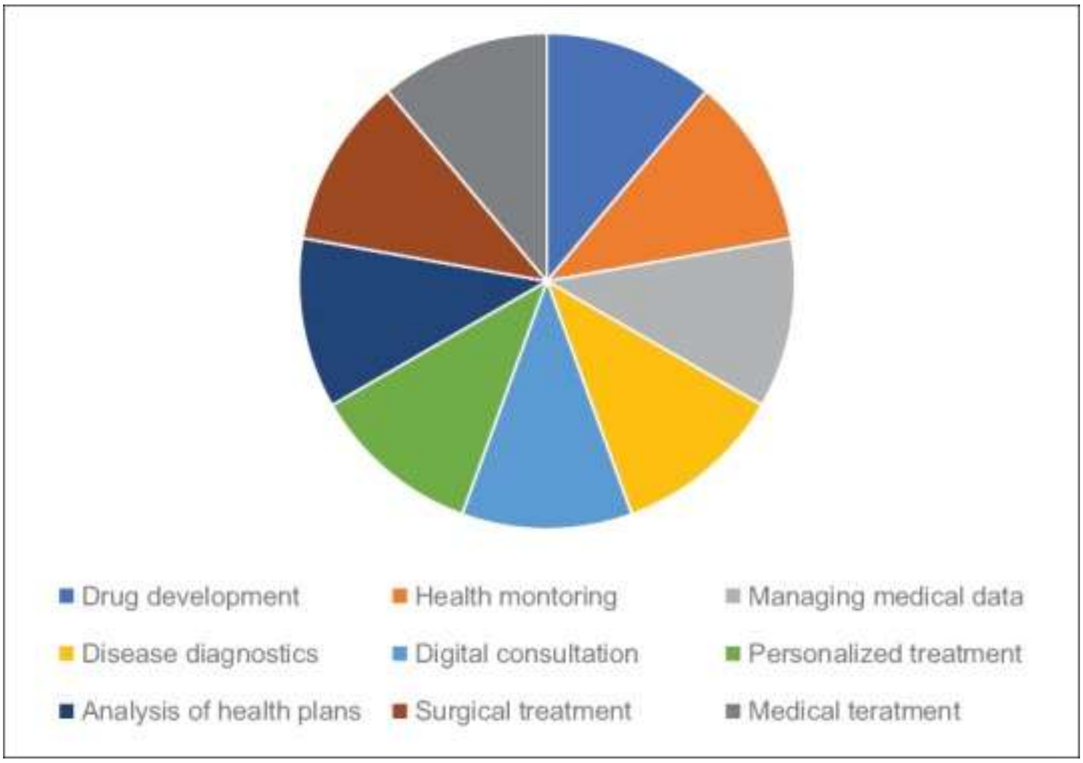


Figure 1 AI applications in healthcare (Amisha, Pathania, & Rathaur, 2019).

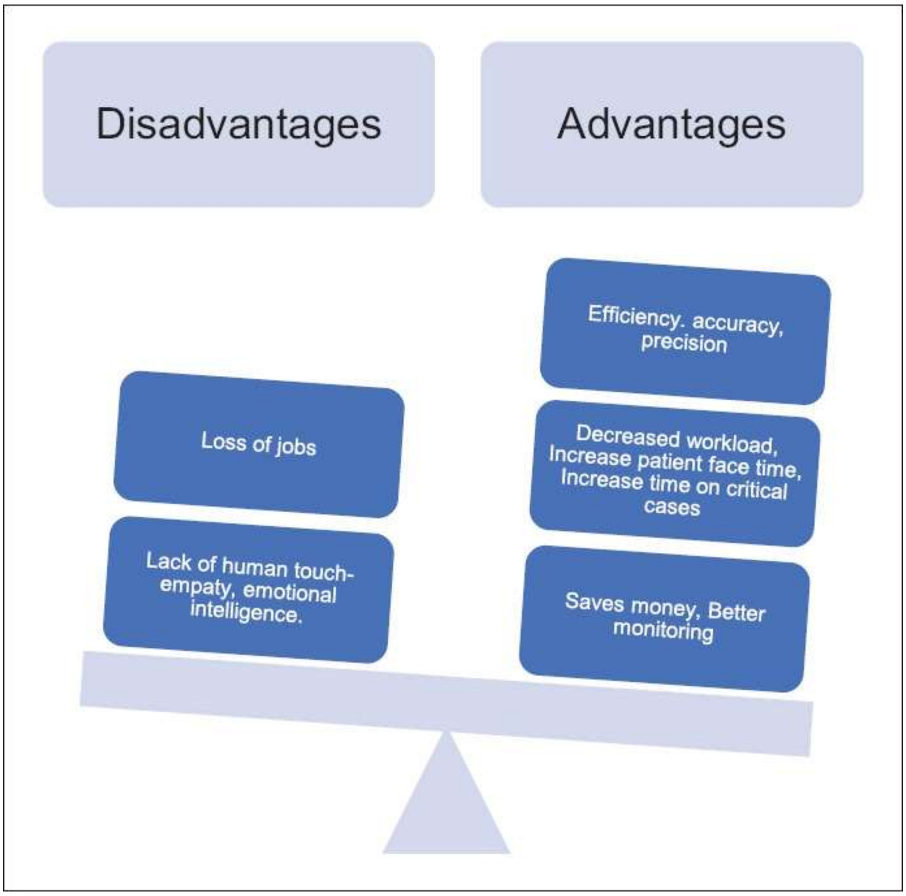


Figure 2 Advantages and disadvantages of AI in healthcare (Amisha, Pathania, & Rathaur, 2019).

Fig 1 shows nine AI applications covering almost all areas of healthcare and medicine. The disadvantage of loss of jobs given in Fig 2 is only a perception. Many findings show that only the skill profiles will change due to AI technology and there may be only a few job losses. Healthcare providers need to upgrade the skills of their employees for AI technology.

Some specific applications of AI in healthcare and medicine were discussed by Davenport and Kalakota (2019). Machine learning (ML), a statistical technique, is used for fitting models to data and learning by training models with data. Different variations of ML are the most used AI techniques. In healthcare, it is used in precision medicine, predicting possible options of successful treatment protocols based on various patient characteristics and the specific treatment context. Supervised learning requires a training dataset for an outcome variable. Neural networks are more complex ML techniques. It is used for applications to categorise like determining the possibility of a patient acquiring a certain disease. Problems are analysed in terms of inputs, outputs and weights of variables or features correlating inputs with outputs. Its analogy with brain functions is weak. Deep learning (DL) is the most complex form of ML. These neural network models have many levels of features/variables to predict outcomes. Several features can be identified through rapid graphic processing and cloud architecture. In healthcare, it is mostly used to identify potential cancerous lesions in radiological images (Radiomics), as an oncological image analysis. Radiomics with DL has higher accuracy than conventional CAD for image analysis. DL, as Natural Language Processing (NLP) is used in speech recognition and speech therapies. Explanation of DL model outcomes is difficult and sometimes impossible to interpret compared to the conventional human interpretation of radiological images. Besides, speech recognition, NLP is used for text analysis, translation, and other language-related matters. Statistical NLP, based on ML (especially, deep learning neural networks) has increased the accuracy of recognition. However, it requires a large 'corpus' or body of language to learn. In healthcare, NLP helps to create, understand, and classify clinical documentation and published research. Analysis of unstructured clinical notes on patients, preparation of reports like those of radiology examinations, transcription of patient interactions and conducting conversational AI are facilitated by NLP. Rule-based expert systems are based on if-then rules. Although their current use is low, in healthcare, they are widely used for clinical decision support. Many providers of electronic health records (EHR) have their own set of rules. The popularity of rule-based expert systems decreased because they require human experts and knowledge engineers to construct a set of rules in a particular domain of knowledge. Up to a point, this is good and easy to understand. When the number of rules becomes several thousand and some of them contradict each other, the expert systems break down. Changing the rules when the knowledge domain changes is difficult and time-consuming. So, they are now replaced with the more efficient ML and DL. Physical robots collaborate with humans to accomplish specific tasks more efficiently. Robots become increasingly intelligent as more AI tools are incorporated into their operating systems (brains). In healthcare, Surgical robots increase the efficiency of surgeons due to increased precision. Robotic process automation (RPA) performs structured digital tasks. They are inexpensive, easy to program and transparent in their actions. No robot is involved in this. It is only computer programmes on servers. RPA uses a combination of workflow, business rules and presentation layer integrated with information systems to perform as a semi-intelligent user of the systems. In healthcare, they are used for repetitive tasks like prior authorisation, updating patient records or billing. RPA can be combined with other technologies like image recognition to extract data from sources like faxed images as input into transactional systems.

There are three main branches of AI applications in healthcare and medicine: physical, virtual and a combination of both. Virtual reality may combine with robots in many applications. However, there are many ethical issues, especially, related to ethical governance. To solve this problem, ethical governance guidelines have already been established by some leading organizations and countries. There are also security risks, for which, many steps related to internet and data security have been implemented by many organizations (Guan, 2019).

The substantial opportunities provided by AI in healthcare were discussed by Matheny, Whicher, and Israni (2020). These include improved patient and clinical team outcomes, reduced costs, and influence on population health. High levels of accuracy in image detection and signal analysis have been reported recently. Currently and in future, much more data are generated than what could be managed by the human cognitive capacity to effectively manage information. AI can help in this respect and support the delivery of personalized health care.

The term “explainability” in the case of AI applications denotes the possibility of reconstructing the reasons for a certain AI presenting some predictions. Interpretability and explainability also denote similar meanings. Research reveals the potential of AI algorithms to outperform humans in certain analytical tasks. But the lack of explainability may affect its practical uses in improving patient and population health. Legal, regulatory, professional, and ethical issues may prevent AI from being used for the benefit of the human community. However, these issues cannot be ignored due to the high risks of AI in certain situations. Amann, et al. (2020) used clinical decision support systems (CDSS) as an example to examine the technological, legal, medical, and patient perspectives. The technical explainability of AI is inherent in the algorithm of the method. If this is hidden (black box), other methods can be used to explain the AI algorithm. There is some trade-off between performance and explainability when old systems are compared with AI methods. There are instances of poor explainability leading to contradictory results from using the same AI method. Explainability should be used as a variable in addition to performance by new AI developers. Only such AI tools should be used. The extent of explainability required for specific AI systems can be prescribed by law. Some of them are high standards of transparency, traceability, acquisition, storage, transfer, processing, analysis, and use, sensitive issues of data privacy and security, patient consent, and autonomy. Informed consent by patients for the use of their data for AI applications and certification and approval of medical tools are two of the explainability aspects. However, the requirement of seeking informed consent leads to some problems. AI can identify novel patterns or find new biomarkers without the need for pre-selection features. If restricted to specific purposes, as required for informed consent, this unique advantage is lost. Informed consent means the patient needs to be explained fully about the processes and algorithms used for decision support systems. But the patient may not understand if full details are given. The best the physicians can do is to explain the input and the output of the AI process and how the output variables affect the patient. The progress in the certification and approval of AI-related medical devices has been slow. Any conflict between innovation and regulation needs to be avoided. From the medical perspective, the two levels of explainability required are the explainability in terms of methods used by the AI to arrive at conclusions and the identification of the specific features of AI for individual prediction. Individual predictions can be checked for false predictions. The first level of explanation is adequate for use in risky clinical cases. For other use cases, second-level explanations may be required to safeguard patients. Clinical validation of the AI-based CDSS system, but not its explainability, has only been considered so far. Prediction errors due to AI bias and random causes can only be reduced and cannot be fully eliminated. This is the reason for the need for explainability from the clinical perspective. From the patient's point of view, the question is whether the use of AI-powered decision aids is compatible with the inherent values of patient-centred care. Shared care between physician and patient is the solution for this. Explainability can solve many ethical issues arising from the use of AI in medicine. These are related to various risks, patient confidentiality, security of data, and professional ethics of physicians and healthcare providers. Overall, when opaque AI algorithms are adopted for CDSS, it may inadvertently revive the old paternalistic concepts of care making patients passive spectators in the medical decision-making process. A new type of care may emerge, in which, physicians become slaves to the output of the AI tools to avoid legal and medical repercussions. Opaque systems might allocate resources erroneously violating their just distribution. Explainability f AI-supported systems ensures patient-centric care and together with clinicians facilitates informed and autonomous decisions about their health. Explainability can promote the just distribution of available resources. Citing Ghassemi, Oakden-Rayner and Beam (2021) that some of the currently available explainable AI are imperfect, providing only partial explanation of their algorithms and therefore seeking other measures, like validation, to enable trust and confidence in black-box models, Reddy (2022) expressed doubt about whether validation by randomised control trials etc would suffice.

Continuing from the basics of the AI tools used in healthcare, Davenport and Kalakota (2019) (see above) pointed out the lack of patient engagement and adherence to the treatment schedules and follow-ups. These problems are increasingly solved by big data and AI by messaging alerts and relevant, targeted content to provoke actions at crucial moments. Another emerging field is the effective designing of a 'choice architecture' to nudge patient behaviour in a more anticipatory way based on real-world evidence. It uses information provided by EHR systems, biosensors, watches, smartphones, conversational interfaces, and other instrumentation in software applications to design recommendations by comparing patient data to other effective treatment pathways for similar cohorts. The recommendations are sent to providers, patients, nurses, call-centre agents, or care delivery coordinators to ensure that the patient follows the treatment recommendations rigorously. In some administrative applications, the use of RPA reduces the non-clinical time spent by nurses. Other applications are claims processing, clinical documentation, revenue cycle management and medical records management. Chatbots are useful for patient interaction, mental health and wellness, and telehealth. But patients are apprehensive about revealing personal information and their poor usability. The possibility of AI leading to job losses is very low due to the high cost of automation technologies, labour market growth and cost, benefits of automation other than simple labour substitution, and regulatory and social acceptance. The current low level of

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AI application and the difficulty of integrating AI into clinical workflows and EHR systems might ensure that there is little impact of AI on healthcare jobs. The use of AI raises ethical issues of accountability, transparency, permission, and privacy. As was pointed out by Amann, et al. (020), explainability is a major factor related to ethical issues. Errors in AI systems and algorithmic bias make it difficult to place accountability. In a systematic review, (Sunarti, Rahman, Risky, Febriyanto, & Masnina, 2021) and in a structured review (Secinaro, Calandra, Secinaro, Muthurangu, & Biancone, 2021) examined the opportunities and risks of AI in healthcare. The findings reiterated the points highlighted by other authors discussed above. The review by Yu, Beam, and Kohane (2018), besides discussing the basic concepts of supervised and unsupervised learning, artificial neural networks, convoluted neural networks with diagrams and some other AI techniques, provided diagrammatic presentations for certain observations made by other reviewers. Some current applications of AI in healthcare have been listed in Fig 3. There are widespread AI applications in all three areas of basic biomedical research, translational research, and clinical practice. The disconnect between the two types of research and clinical practice is obvious. The comparison of human and AI evaluations in Fig 4 does not endorse the superiority of AI evaluations entirely. In many respects, human evaluation is superior to AI evaluation. Fig 5 shows the decreasing role of clinicians in taking decisions on patient care with increasing automation using AI. When fully automated, there is no clinician at all. According to the information in Fig 6, at various levels of clinical integration with AI, the relative reliability and precision of diagnosis and treatment will vary.

Basic biomedical research	**Translational research**	**Clinical practice**
Automated experiments	Biomarker discovery	Disease diagnosis
Automated data collection	Drug-target prioritization	Interpretation of patient genomes
Gene function annotation	Drug discovery	Treatment selection
Prediction of transcription	Drug repurposing	Automated surgery

Figure 3 Some current applications of AI in healthcare (Yu, Beam, & Kohane, 2018).

Approaches	Model comprehensibility	Performance	Reproducibility	Dependency on prior knowledge	Developme and trainin costs[a]
Human evaluation	High	Moderate or high	Moderate	High	High
Rule-based algorithms	High	Moderate or high	High	High	Moderate high
Feature-based machine-learning methods	Moderate or high	Moderate or high	High	Moderate[b]	Moderate
Deep artificial neural networks	Low or moderate	High	High	Low	Moderate

Figure 4 Comparison of human AI evaluations (Yu, Beam, & Kohane, 2018).

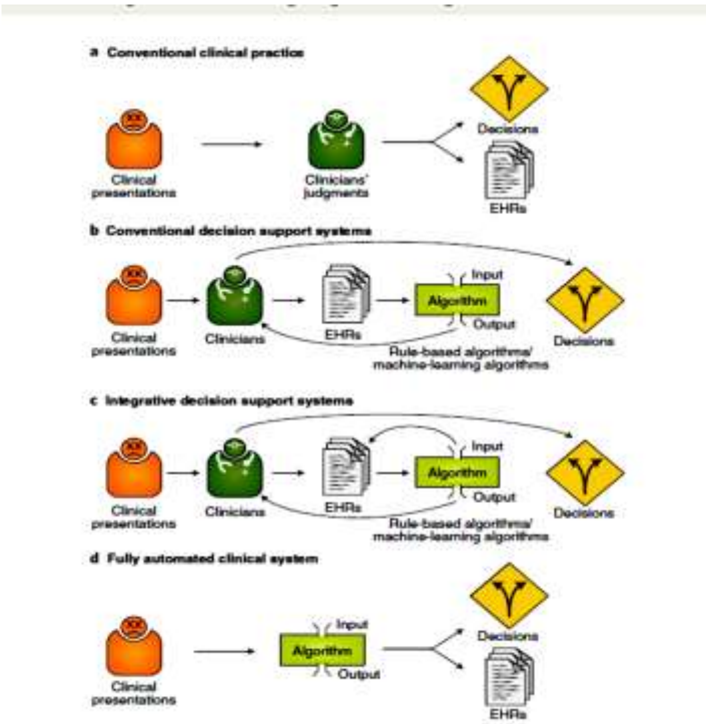

Figure 5 Comparison of information flows in different levels of automation of clinical decision support systems (Yu, Beam, & Kohane, 2018).

	Areas where AI performance is more reliable than that of a human expert	Areas where AI performance is at the expert level	Areas where AI performance is reasonable	Areas where AI performance is not yet good enough	Areas where the nature of the clinician-patient interaction is fundamentally different from that of the AI-patient interaction
Examples	Serum analyser; alert systems (such as drug-drug interaction checkers)	Assessment of certain radiology images (for example, annotation of cardiovascular MRI images or evaluation of X-ray images for distal radius fracture); dermoscopic melanoma diagnosis; fundus photograph evaluation for DR	ECG reading	Surgery; full interaction with patients	Emotional support and rapport
Potential clinical integrations	Delegate to AI	AI does the majority of the task, clinicians confirm the diagnosis	AI does a portion of the task (such as screening), clinicians confirm the diagnosis	Clinicians lead the clinical evaluations and intervention, AI assists in routine sub-tasks	Clinicians continue to provide the service

Figure 6 Clinical integration of AI at different development stages (Yu, Beam, & Kohane, 2018)

A multi-step approach for building a reliable and effective AI-supported system in healthcare was proposed by Bajwa, Munir, Nori, and Williams (2021) (Fig 7). This was adapted from a more truncated version of Wiens, et al. (2019).

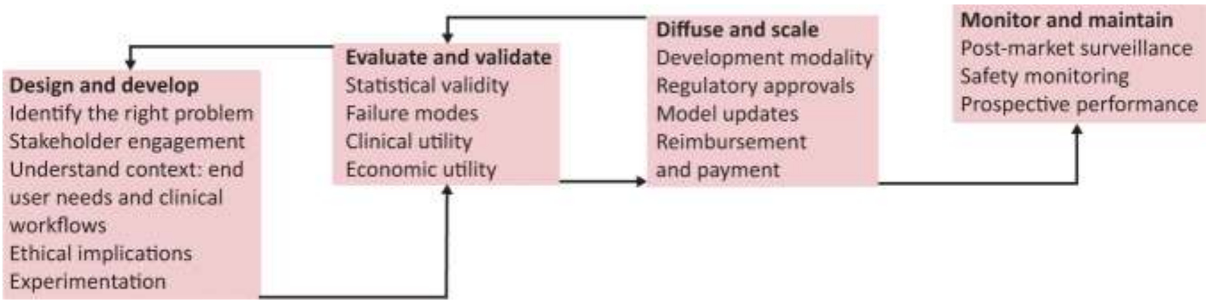

Figure 7 Multi-step iterative approach for building a reliable and effective AI-augmented healthcare system (Bajwa, Munir, Nori, & Williams, 2021).

The stakeholders identified by(Wiens, et al. (2019) are knowledge experts (clinical experts, AI researchers, health information and technology experts, and implementation experts), decision-makers (hospital administrators, institutional leaders, regulatory agencies and the government), users (nurses, physicians, laboratory technicians, patients, family and friends). Failure modes include a lack of explainability. Regulatory approvals should be based on the extent of utility and explainability of the device. The effectiveness of the first three stages depends on the last of performance outcomes.

The benefits of AI in healthcare systems proposed by Eggers, Schatsky, and Viechiniki (2017) were diagrammatised by(Aung, Wong, and Ting (2021), presented in Fig 8. Eggers, Schatsky and Vienchiniki (2017) had given the names of the four benefits and brief explanations only. AI relieves extra workloads of clerical duties etc and replaces administrative jobs of doctors and nurses to focus more on patients. Splitting clinical jobs by early screening to avoid unnecessary admissions etc is a third benefit. Some healthcare processes can be augmented by AI to increase their precision and efficiency. AI drawbacks (Fig 9) pervade data acquisition, technology development, implementation, and ethical and social factors.

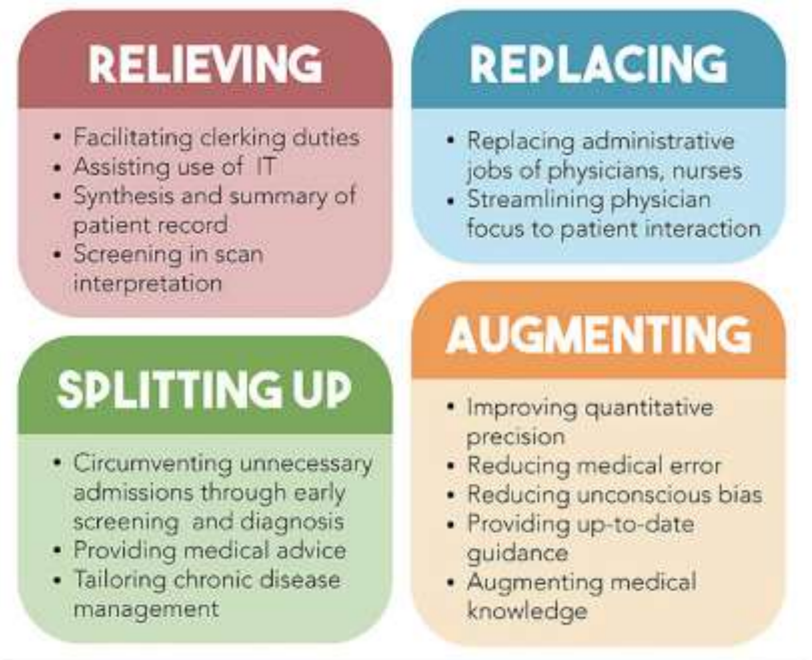

Figure 8 Four benefits of AI in healthcare systems (Aung, Wong, & Ting, 2021).

The drawbacks of using AI in healthcare systems in multiple aspects were also presented by Aung, Wong, and Ting (2021). Various applications of AI in healthcare systems were elaboratively reviewed by Bohr and Memarzadeh (2020) and by Briganti and Le Moine (2020) supporting the points highlighted in the above discussions. Ethical issues of adopting AI in healthcare were discussed by Rigby (2019) supporting the issues highlighted in the above-discussed papers. A diagrammatic representation of areas in which AI can be used in healthcare was discussed (Manne & Kantheti, 2021).

The focus of the paper by Ahmed, Mohamed, Zeeshan, and Dong (2020) was AI and ML-based systems bridging multiple domains in a secure environment for heterogeneous healthcare data analysis and visualization. Multifunctional ML platforms for clinical data extraction, aggregation, management and analysis can help clinicians by efficiently stratifying patients to understand specific scenarios for optimised decision-making. A diagram of this concept has been presented and discussed by the authors. The diagram shows that AI can address key issues in healthcare like misdiagnoses, overtreatment, one-size-fits-all approaches, repetition, decreased productivity, under-utilized data, and significant cost and spending. AI identifies key biomarkers to provide economic and personalized treatment by intelligently analysing heterogeneous data. How ML algorithms collect data from different sources and integrate them was shown by authors.

Interviews with 40 diverse French stakeholders by Laï, Brian, and Mamzer (2020) revealed diverse opinions on the usefulness of AI in healthcare along the lines of their backgrounds. Healthcare professionals were only concerned about the safest and best patient care. AI providers saw government regulations limiting their access to individual health data as an obstacle to the development of new AI tools. Institutional participants recognised the significance of their role in regulatory issues. Other, independent participants were concerned about the sustainability of the balance between health, social justice, and freedom. Researchers had a more pragmatic view on a better transition from research to practice.

A sequential guide for implementation for AI adoption by healthcare institutions was provided by Chen (2020) in the order: consideration of both short-term and long-term goals, the establishment of leadership, team, culture, collaborations for successful implementation, selection of appropriate AI tools, approaches and strategies, formation of a good data strategy for patient insights, retraining ML algorithms and validating AI applications with data and patients from the local organizations, determining the contexts and protocols for safe use of AI technology, and establishing performance standards to measure success. A diagrammatic scheme for the delivery of AI for use in healthcare was presented and discussed by Li, Asch, and Shah (2020). The general content of the scheme is like the guide by Chen (2020) listed above.

The steps in Fig 13 involve process improvement, design thinking, and implementation science. Involving a multidisciplinary group of stakeholders throughout the process is important. The process includes analyses to verify that the model's execution and runtime characteristics are in line with the logical needs of the new workflows. Evaluation should include both implementation and the outcomes including sociotechnical aspects. Roles and responsibilities for the AI system and the healthcare components need to be allocated properly.

The results of 11 studies on consumer receptivity to AI in healthcare were presented by Longoni, Bonezzi, and Morewedge (2019). A uniqueness neglect hypothesis was formed for this purpose. Consumers are possibly more reluctant to utilize healthcare delivered by AI providers than healthcare delivered by comparable human providers, even if they have explicit information about the performance of both providers. This occurs due to the concern that an automated provider will neglect one's unique characteristics, circumstances, and symptoms. This concern is termed uniqueness neglect. Uniqueness neglect emerges from a mismatch between two fundamental beliefs. Consumers think themselves to be unique and different from others. They perceive machines can operate only in a standardised way treating every case similarly due to their cognitive inflexibility. In healthcare, people perceive their health-related characteristics to be more unique than the same characteristics in other people, as in the example, I caught a cold; You caught the cold. In the case of AI, this belief transforms into considering medical care delivered by AI providers as standardized and calibrated for an average patient. Thus, they believe that their unique factors are neglected by AI. Eleven studies were used by the authors to test the uniqueness hypothesis, using different methods. The results revealed several points. More the uniqueness perception, the higher the resistance to AI. Consumers were reluctant to utilise healthcare provided by AI in separate and joint evaluations. Consumers were less likely to utilise healthcare (study 1), exhibited lower reservation prices for healthcare (study 2), were less sensitive to differences in provider performance (studies 3A-3C), and derived negative utility if the provider was automated rather than human (study 4). Resistance to medical AI was stronger among consumers who perceive themselves to be more unique (study 5). Uniqueness neglect mediated resistance to medical AI (study 6), was eliminated when AI provided personalised care (study 7), to consumers other than the self (study 8), or only supported, rather than replaced, a decision made by a human healthcare provider (study 9). In the 15 focus groups with patients, they expressed multiple concerns related to the safety of AI, threats to patient choice, the potential for cost increases, data-source bias, and data security. Patient acceptance of AI depended on solving these possible harms (Richardson, et al., 2021). Semi-structured interviews with 24 health professionals related to oncology by Gillan, et al. (2019) revealed that the participants perceived the advantages of AI as useful concerning time-consuming repetitive tasks like defining targets, generating treatment plans and quality assurance. Outcomes data and adaptive planning could be incorporated into clinical decision-making. Changing workload would require changing skills, prioritisation of plan evaluation over generation and increasing interprofessional communication. AI could reduce the need for some jobs by displacement rather than by replacement.

To address the lack of reporting standards for AI in healthcare, Hernandez-Boussard, Bozkurt, Ioannidis, and Shah (2020) proposed MINIMAR (MINimum Information for Medical AI Reporting) and prescribed the requirements to meet the standards consisting of many variables.

Discussions

Except for three, all other papers were discussions based on a literature review. Most papers followed the pattern of first defining Artificial Intelligence, followed by a description of some tools like ML and then some specific applications of AI tools in healthcare with or without diagrams to aid explanations. Most papers also discussed challenges in implementing AI in healthcare and medicine. Ethical issues were discussed in many papers. The exception papers used interviews (Gillan, et al., 2019), focus groups (Richardson, et al., 2021), and multiple methods (Longoni, Bonezzi, & Morewedge, 2019) to inform the perceptions and hesitation to accept AI in patient care by common communities (Longoni, Bonezzi, & Morewedge, 2019), patients (Richardson, et al., 2021), and medical professionals including AI researchers (Gillan, et al., 2019). All, except researchers, had certain reservations about accepting AI for patient care. There are also apprehensions about the privacy and security of individual patient data in AI.

The trends of discussions in the papers show that AI has not been fully integrated with patient care and healthcare providers' requirements. Hence, research should now focus on this aspect rather than continuing with developing new AI tools and applications. There is a serious issue of explainability, which is related to ethical issues. The AI integration research should include explainability also. While this is the problem affecting large-scale adoption of AI in healthcare on the supply side, the acceptability of AI in healthcare is low among patients, healthcare professionals and the common community on the demand side. There is resistance to AI among them due to these problems. These are also the challenges of AI adoption in healthcare. More research using high-quality enquiry methods is required to add to the three papers on these aspects.

Conclusions

Although AI tools and techniques are useful for many aspects of healthcare, their adoption rate is low. Lack of explainability, ethical issues, concerns about the privacy and security of patient data and AI not being integrated fully with healthcare systems are affecting the acceptability of AI by patients, healthcare professionals, and the common people. These are the reasons for the low adoption rate by healthcare organisations. Future research should shift to addressing these problems and finding effective solutions.

The Google Scholar pages were rich with as many papers as each page displayed. This created some difficulty in identifying suitable papers for this review. Since almost all papers fell into the common pattern of discussions based on literature, no quantitative analysis was possible. This was the reason to label this paper as a systematic qualitative review. Most papers, being discussions, did not mention any limitations. The three research papers were of good quality. Therefore, it was not possible to list the limitations of each paper.

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