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A review of AI and ML applications in healthcare management

Hanan Falah S Alqahtani[1]

Mohamed Ali M Altalea

Saad Mojeb M Alshahrani

[1]Corresponding Author Email: Hano2019ff@icloud.com

Abstract

Research has been supporting the healthcare sector by developing digital tools like AI to transform the sector rapidly towards evidence-based, patient-centric and error-free quality care. Many reviews have been published on research done on this topic. This review attempts to update the current knowledge and discover the potential for future scope of AI and ML applications in healthcare management.

The search for papers on the databases of NCBI, CNAHL and World of Science was augmented with a search on Google Scholar. The papers identified were screened through the PRISMA flow process. Finally, 20 papers could be selected for this review.

Overall, the review provided a comprehensive picture of AI, its applications, usefulness, barriers and challenges to address and impact on evidence-based personalised healthcare quality. Five reviews discussed the status and potential of AI in healthcare. They also discussed the challenges and solutions to them. The role played by AI in managing COVID, especially in developing countries, is notable. India dominated among the countries of the study; empirical studies used various methods like surveys, interviews, focus groups and mixed approaches. Methodological limitations of various types were noted as limitations in most papers. Most papers provided recommendations either for research or for practice, and rarely both. The 20 reviewed papers were mostly medium to high quality.

Some limitations of this review and recommendations for research and practice have been given.

Keywords: AI, ML, Healthcare, Evidence-based, Error-free, Patient-centric, Challenges and barriers.

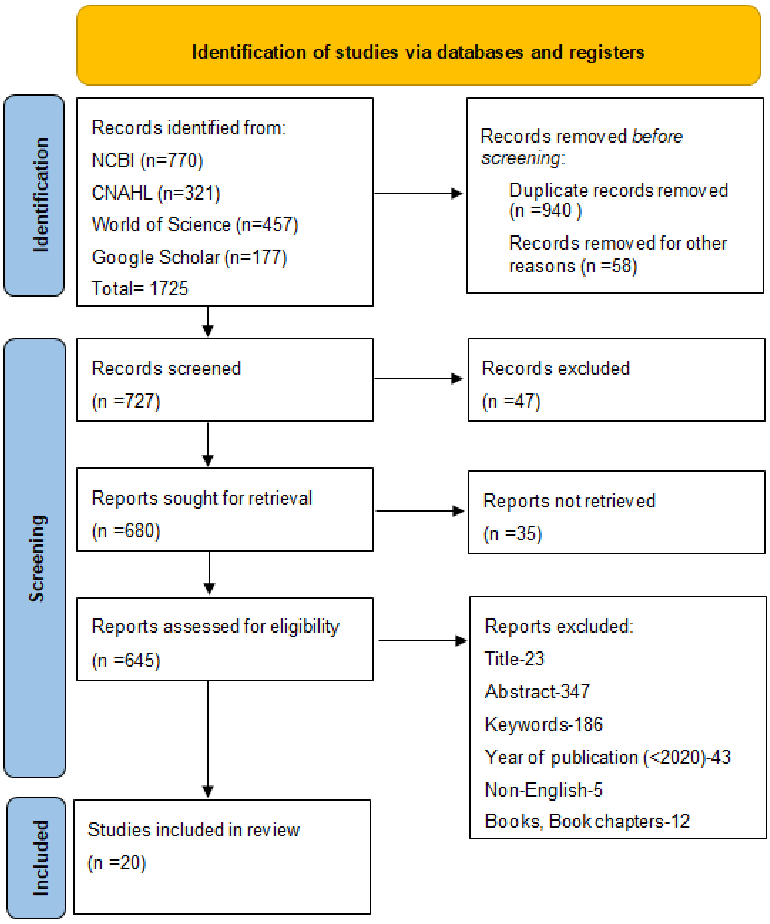
Introduction

The healthcare sector has been transforming rapidly, using digital tools all over the world. The main digital tools are artificial intelligence (AI) and machine learning (ML). These digital tools are used in healthcare management to automate administrative tasks, such as scheduling patient appointments with doctors, managing patient records, processing insurance claims, and managing patient flows. Additionally, chatbots provide administrative support, while data analysis enables rapid diagnosis, better treatment plans, and the prediction of pandemic outbreaks. It is also used for robotic surgery and patient sentiment analysis. Consequently, evidence-based patient-centric, error-free healthcare has become possible. This paper aims to review some of the recent trends in these areas.

This paper is organised as follows: after this Introduction section, the Methodology followed for this review, Results, Discussions, Conclusions, Limitations and Recommendations for research and practice are described serially.

Methodology

NCBI, CNAHL, World of Science and Google Scholar were searched to identify the relevant papers. The papers underwent several screenings through language (English only), titles, abstracts, keywords, authorship, country, year of publication, methodology, limitations and overall quality (0 to 5 scale), and recommendations for future research and practice. Books, book chapters, dissertations, and comments were excluded. The screening processes were done using the PRISMA process. Finally, 20 papers (five reviews and 15 empirical studies), published during 2021-2025, were selected for this review. The results were tabulated in an Excel file for synthesis.



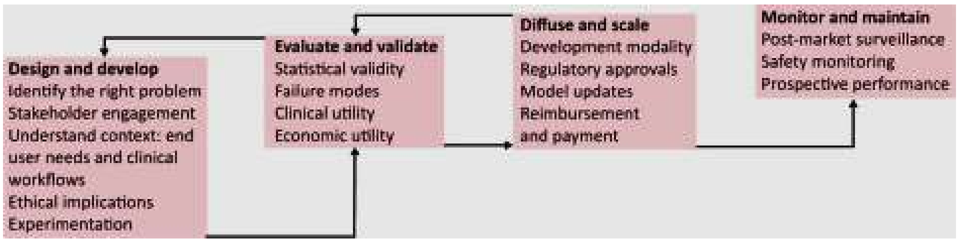
Results

Reviews

According to Bajwa, Munir, Nori, and Williams (2021) these applications are disruptive science for evidence-based healthcare for every patient. The authors presented a multistep iterative approach to build an effective and reliable AI-augmented healthcare system, as shown in Fig. 1.

Figure 1

A multistep iterative approach to build an effective and reliable healthcare system



Thus, the stages are design and develop, evaluate and validate, diffuse and scale, monitor and maintain. The stakeholders in the entire process are physicians, caregivers, patients, specialists, administration employees, the department of health, universities and other educational institutions, and financial institutions. The near-future developments include AI, which can reason in the next 5-10 years, AI is expected to use more efficient algorithms requiring less data to train, capable of using unlabelled data, and combine disparate structured and unstructured data, including imaging, electronic health data, multi-omics, behavioural and pharmacological data. Healthcare organisations and medical practices will transform from being adopters of AI platforms to becoming co-innovators with technology partners in developing novel AI systems for precision therapeutics. In the longer term of >10 years, as AI systems grow increasingly sophisticated, they will empower healthcare technologies to realise the vision of precision medicine through enhanced AI-driven care and integrated health networks. This evolution will transform healthcare from a uniform, reactive model into a proactive, personalised, and data-informed approach to disease management, resulting in better patient outcomes, enriched clinical and patient experiences, and more efficient, cost-effective care delivery. AI could be applied to the remote monitoring of patients through wearable sensors as an intelligent healthcare system. Healthcare clinics, hospitals, social care providers, patients, and caregivers will be seamlessly integrated into a unified, interoperable digital ecosystem powered by passive sensing technologies and ambient intelligence. Patients will be empowered to recognise symptoms and receive guidance on next steps within the community and primary care environments. AI-powered chatbots, when paired with wearable technologies like smartwatches, can deliver personalised insights to both patients and caregivers, supporting healthier behaviours, better sleep patterns, and overall wellbeing. Some ambient sensing applications without the need for peripherals are Emerald, Google Nest, and NDAX. The broader integration of AI into healthcare systems faces challenges like span data accessibility and integrity, limitations in technical infrastructure, organisational readiness, and the need for ethical and responsible implementation alongside critical concerns around safety and regulatory compliance.

To explore how AI influences healthcare management in operational, strategic, and emergency response domains, and to identify variations in the impact of AI on healthcare management based on temporal and geographical contexts (Santamato, Tricase, Faccilongo, Iacoviello, & Marengo, 2024), Prisma reviewed 79 papers between 2019 and 2023, which also covers the COVID period. AI's role was evident in enhancing quality assurance, resource management, technological innovation, security, and the healthcare response to the COVID-19 pandemic. AI's positive influence can be observed in the case of operational efficiency and strategic decision-making. The challenges are related to data privacy, ethical considerations, and the need for ongoing technological integration. There are further opportunities for targeted interventions to optimise AI's impact in current and future healthcare landscapes. The authors presented targets and features of predictive models. Some results on ML methods showed Neural Networks and Random Forest as the best models. This is shown in Figure 2. Quality predicted

COVID-19 with 80% accuracy. The limitations are that the traditional machine-learning techniques, like logistic regression, though valued for their interpretability, fall short in representing the intricate nonlinear patterns present in data. Moreover, the application of the SHAP (SHapley Additive exPlanations) framework remains underexplored in the context of large-scale datasets and highly nonlinear models, thereby constraining the clarity and transparency of decision-making processes in such complex scenarios. Recommendations include supporting responsible AI adoption in healthcare, emphasising a collaborative approach that includes all stakeholders, robust data privacy and security, and continuous training for healthcare professionals, and promoting ongoing research to improve AI capabilities and address emerging ethical challenges.

Figure 2

Comparison of models

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.821	0.536	0.501	0.475	0.536	0.398
Neural Network	0.811	0.536	0.528	0.529	0.536	0.406
Random Forest	0.762	0.571	0.528	0.495	0.571	0.446
kNN	0.747	0.536	0.510	0.519	0.536	0.417
Gradient Boosting	0.730	0.429	0.422	0.424	0.429	0.273
Naive Bayes	0.818	0.500	0.477	0.502	0.500	0.373
SVM	0.760	0.518	0.472	0.448	0.518	0.367

To explore the different applications of AI and ML, highlighting their role in predictive modelling, drug repurposing, lead optimisation, and clinical trials and AI's contributions to regulatory compliance, pharmacovigilance, and personalised medicine, while addressing ethical and regulatory considerations, Kandhare, Kurlekar, Deshpande, and Pawar (2025) reviewed the literature to evaluate the influence of artificial intelligence and machine learning across multiple sectors of the pharmaceutical industry. This analysis encompassed scholarly articles, case studies, and industry publications to investigate AI-enabled innovations in predictive analytics, computational drug design, clinical trial optimisation, pharmacovigilance, and supply chain operations. Artificial intelligence (AI) and machine learning (ML) are driving transformative advances across pharmaceutical research and development. Key innovations include improved target identification, accelerated drug discovery via generative models, and enhanced structure-based design through molecular docking and QSAR techniques. In clinical trials, AI facilitates patient recruitment, outcome prediction, and real-time monitoring. Manufacturing and supply chain operations benefit from AI-enabled predictive maintenance, process optimisation, and inventory control. In personalised care, AI supports precision treatment through genomic analysis, biomarker identification, and diagnostic tools. AI and ML are reshaping the pharmaceutical landscape, offering novel solutions in drug development, regulatory processes, and patient care. While these technologies improve therapeutic outcomes and operational efficiency, they also introduce ethical and regulatory complexities that demand transparent and accountable governance. Sustained progress will depend on interdisciplinary collaboration to ensure responsible and equitable integration of AI across the sector.

The authors have provided a diagram of the AI and ML applications in drug discovery, as shown in Figs. 3 and 4.

Figure 3

AI, DL and ML applications in drug discovery (Kandhare, Kurlekar, Deshpande, & Pawar, 2025).

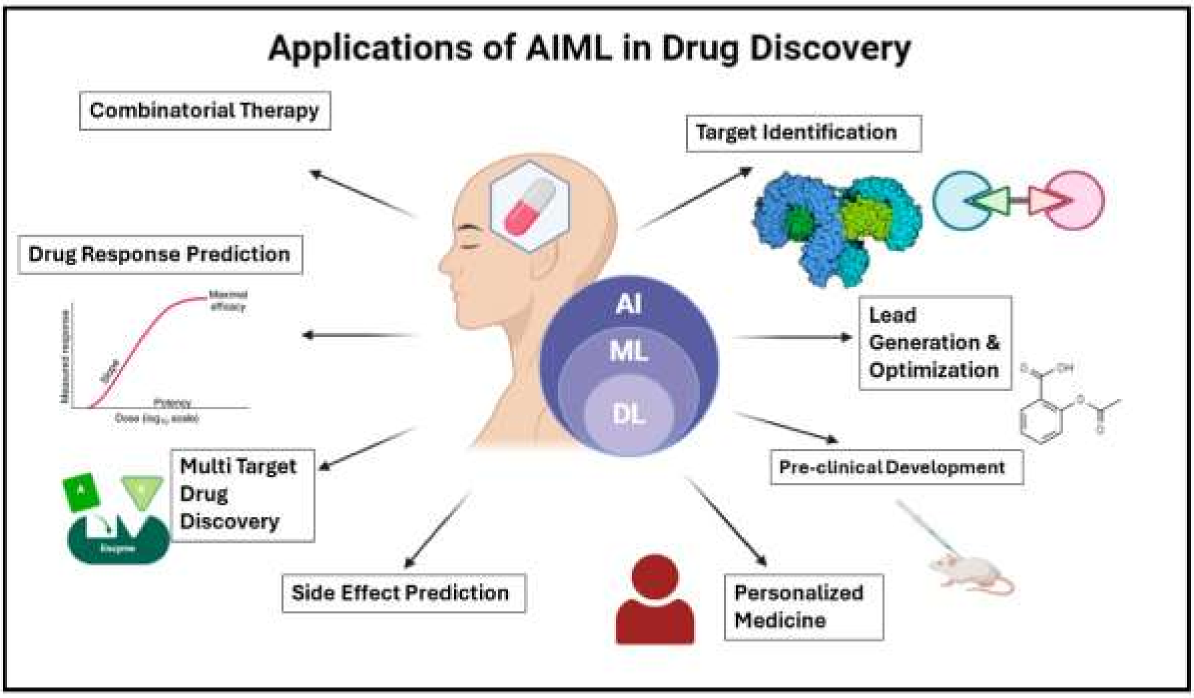
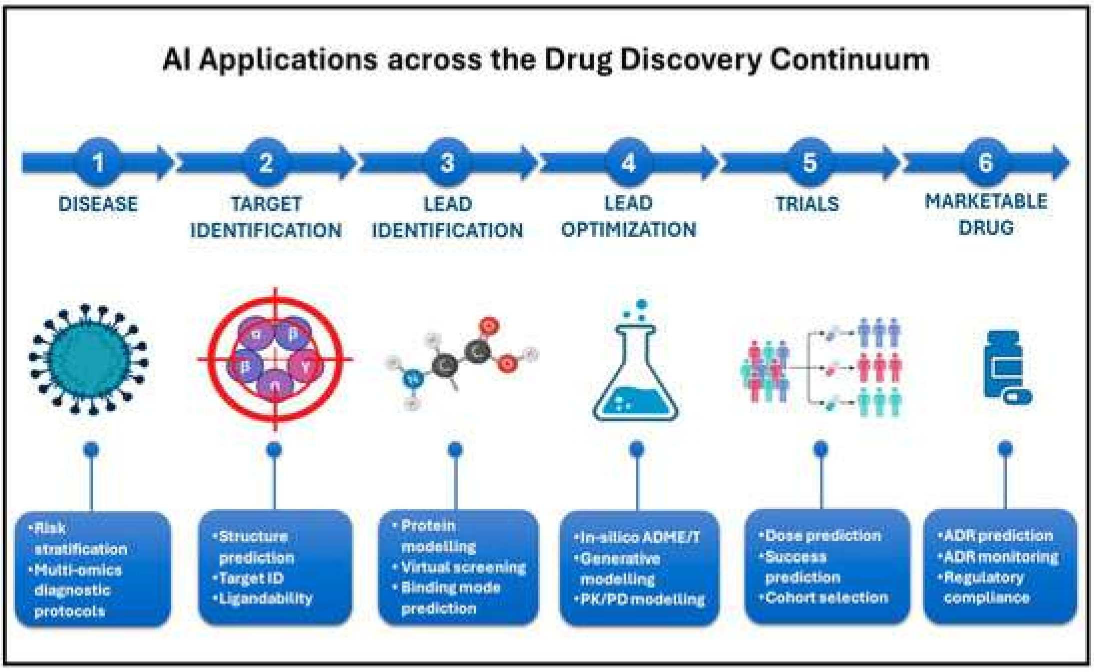


Table 4

AI applications across the drug discovery continuum (Kandhare, Kurlekar, Deshpande, & Pawar, 2025)



A diagram of Quantitative Structure-Activity Relationship (QSAR) modelling is available in Fig.5.

Figure 5

Integration of AI/ML in QSAR workflow (Kandhare, Kurlekar, Deshpande, & Pawar, 2025)

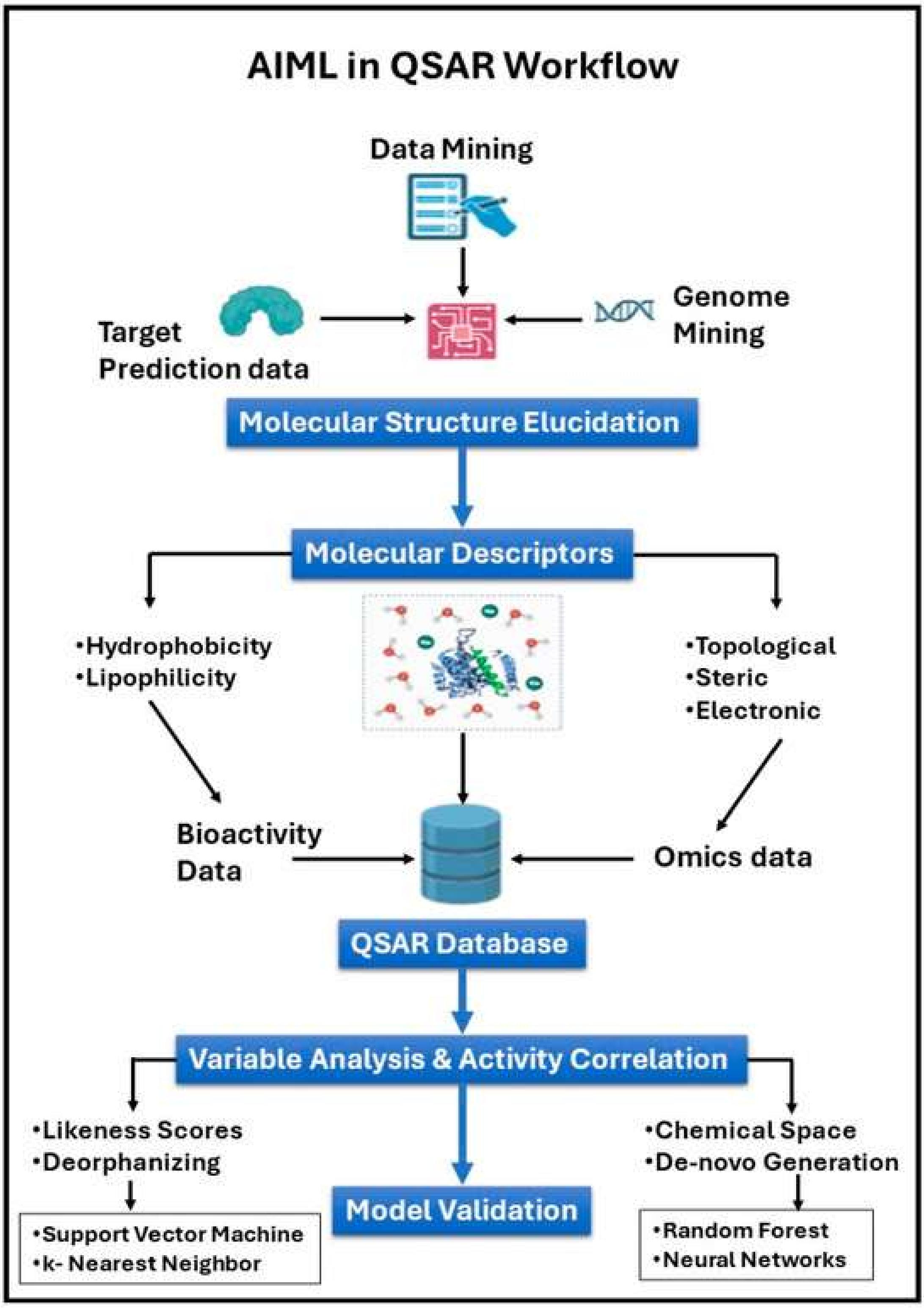
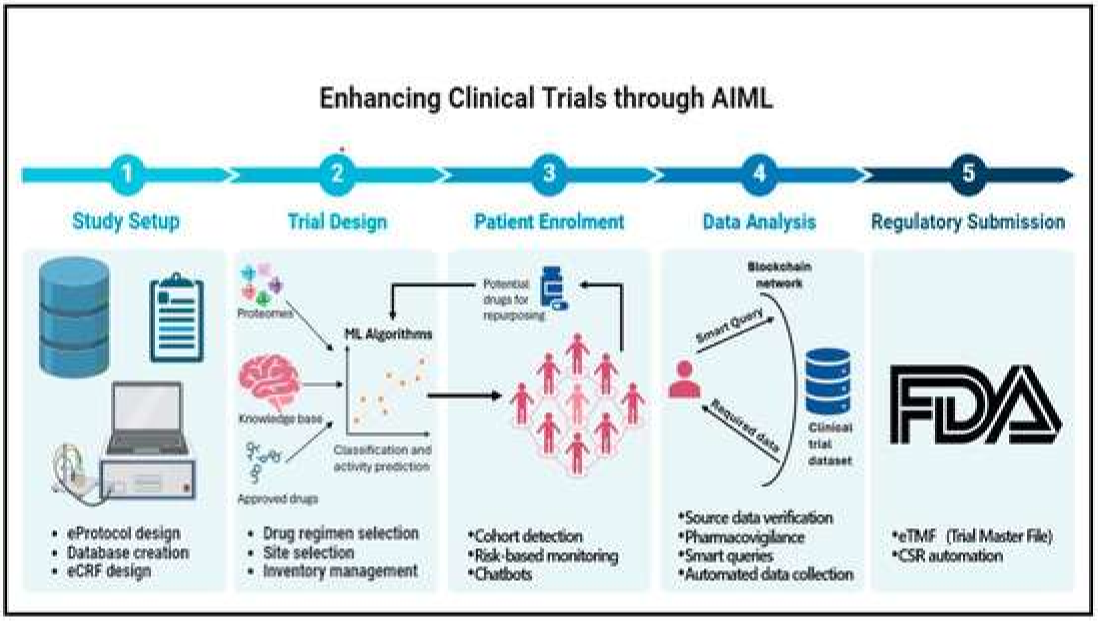


Fig.6 shows Various AI tools and their uses across the clinical trial process.

Figure 6

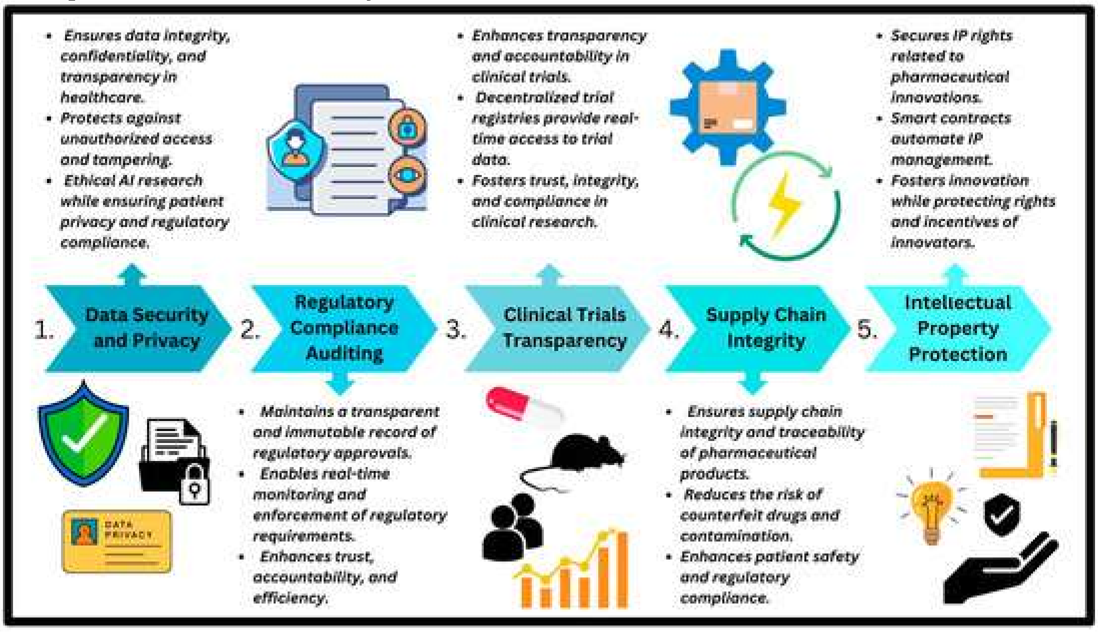
Various AI tools and their uses across the clinical trial process (Kandhare, Kurlekar, Deshpande, & Pawar, 2025)



In Fig.7, Applications of blockchain in the pharmaceutical industry.

Figure 7

Applications of blockchain in the pharmaceutical industry (Kandhare, Kurlekar, Deshpande, & Pawar, 2025)



Arowoogun, Babawarun, Chidi, Adeniyi, and Okolo (2024) comprehensively reviewed data analytics in healthcare management, focusing on utilising big data for decision-making. The authors explored the historical evolution of data analytics, emphasising its increasing importance in clinical support, resource allocation, and operational efficiency within the healthcare sector. The paper discussed fundamental concepts, methodologies, and emerging trends, including integrating artificial intelligence, real-time analytics, and the influence of wearable technologies. The main challenges are data quality, privacy, and interoperability. Data analytics in healthcare began with the integration of electronic health records (EHRs) and basic data systems, initially focused on retrospective analysis of structured clinical data. The emergence of big data technologies in the early 21st century marked a pivotal shift, enabling healthcare organisations to process vast volumes of structured and unstructured data, including medical imaging and genomics. Enhanced computing power and scalable storage facilitated deeper insights into patient health and treatment efficacy. Machine learning further advanced the field by enabling predictive analytics and supporting personalised medicine. The evolution from descriptive to predictive and prescriptive analytics marks a pivotal transformation in healthcare data utilisation. Descriptive analytics established the groundwork by summarising historical patterns, while predictive analytics enabled foresight into emerging trends. Prescriptive analytics advanced this trajectory by offering actionable recommendations to optimise clinical and operational decisions. This continuum of analytical sophistication continues to reshape the healthcare landscape, equipping professionals with data-driven tools to enhance patient outcomes, streamline care delivery, and bolster system-wide efficiency. The sustained integration of advanced methodologies reflects a deepening commitment to innovation, solidifying data analytics as a cornerstone of modern healthcare decision-making. The main theories and frameworks used in this area are formation Lifecycle Management, technology Acceptance Model (TAM), and Decision Support Systems (DSS). The challenges are data quality, data privacy and security, resource constraints, interoperability, resistance to change and ethical concerns. The future trends are that the adoption of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare analytics is rapidly advancing, set to transform how decisions are made across the sector. Sophisticated algorithms capable of processing vast and complex datasets are increasingly vital for uncovering nuanced patterns and delivering highly accurate outcome predictions. Also, preventive healthcare, real-data analytics, wearable technology, remote monitoring, blockchain technology, and the use of social determinants in healthcare. According to the authors, future research should prioritise data governance, technological advancements, and socioeconomic impact.

Zuhair, et al. (2024) reviewed the deployment of AI in healthcare systems across developing nations, aiming to highlight its importance by thoroughly examining current progress, existing limitations, the state of AI adoption, ongoing barriers, and forward-looking solutions to overcome these hurdles. Articles from PubMed, Google Scholar, and Cochrane were searched from 2000 to 2023 with keywords including AI and healthcare, focusing on multiple medical specialities. The expanding role of artificial intelligence in clinical diagnosis, prognostic modelling, patient care, hospital operations, and community health initiatives has significantly enhanced healthcare system efficiency. This impact is particularly notable in high-volume and resource-constrained settings across developing countries, where quality of care is frequently compromised. Nonetheless, the full potential of AI remains underutilised due to persistent barriers such as low adoption rates, lack of standardised implementation frameworks, prohibitive costs associated with equipment installation and maintenance, and infrastructural limitations, including inadequate transportation and connectivity. Despite the challenges, AI has a high potential in the present and the future of healthcare. The authors recommend ongoing education for researchers and clinicians, especially in developing countries. Higher allocations of resources for infrastructure and training, development of standardised guidelines and governance regulations, disability inclusion, user-friendly AI systems for rural health workers, and collaboration between developed and developing countries.

Empirical studies

A survey of 301 healthcare professionals by Mohan, Kumar, Annam, Yadav, and Prashanth (2023) showed that the key factors shaping the transformative role of

Artificial Intelligence (AI) and Machine Learning (ML) in healthcare operations include early disease detection and predictive analytics, accelerated drug development and discovery, personalised treatment strategies, and enhanced remote monitoring and telemedicine capabilities.

Al-Dmour, Al-Dmour, Amin, and Al-Dmour (2025) proposed a comprehensive model to understand the antecedents of healthcare outcomes, including the impact of perceived ease of use, perceived usefulness, and organisational capabilities. A survey of 288 Jordanian healthcare professionals, analysed using partial least squares modelling, showed that AI technologies substantially enhance diagnostic precision and treatment planning. At the same time, big data analytics contribute to improved operational efficiency and patient care delivery. However, the differential impact of AI across various healthcare processes remains comparatively modest. The study underscores the pivotal role of robust organisational capabilities in facilitating the effective adoption and integration of AI and big data analytics. Moreover, perceived ease of use and perceived usefulness emerge as key mediators in the relationship between technology adoption and healthcare outcomes. A nuanced understanding of the dynamic interplay between AI, big data analytics, and healthcare delivery is essential for policymakers, healthcare administrators, and technology developers seeking to formulate strategies that advance both patient outcomes and system-wide efficiency. The authors used the Technology Acceptance Model (TAM) and Resource-Based View (RBV to interpret the results. Limitations include focus on a single country, possible bias due to convenience sampling, limited focus on AI and big data analytics, and limiting the analysis to direct and mediating effects. The authors recommend investing in user-friendly AI and big data analytics tools, enhancing organisational capabilities, and providing comprehensive training for healthcare professionals. Future research should extend this study to different cultural contexts to validate the findings and contribute further to the literature on AI and healthcare.

Results of a survey of 300 and four surveys of 50 each of NHS (UK) participants by Chakravarthi, Kandi, Maheswaran, Gupta, and Chakravarthy (2022) showed that in the National Health Service (NHS UK), Artificial Intelligence (AI) applications are predominantly concentrated in administrative functions and data science domains. AI technologies in healthcare are broadly categorised into three types: rule-based systems, machine learning (ML), and deep learning (DL). Among these, recent research highlights a growing preference for deep learning approaches, attributed to their superior performance and lower update costs. Nonetheless, key challenges persist, including the management of large datasets, algorithmic inaccuracies, and data security concerns, all of which are addressed in this study. The paper concludes by outlining potential solutions to these empirical challenges, offering actionable insights for future implementation.

Pazhayattil and Konyu-Fogel (2023) surveyed 304 participants from the US pharmaceutical sites registry, representing all sectors of the industry. The study revealed distinct trends and preferences shaping the pharmaceutical sector's adoption of emerging technologies. The first hypothesis, tested using the Kruskal-Wallis method, confirmed a statistically significant variation in the perceived applicability of Rogers's diffusion of innovation theory within the industry. The second hypothesis, evaluated through Kendall's τ, indicated a strong consensus that the convergence of machine learning and AI is imminent. For the third hypothesis, Spearman's rank correlation analysis identified key domains yielding high returns on investment, including operational efficiency, product quality, supply chain integrity, market identification and penetration, as well as engineering and maintenance. The fourth hypothesis, also assessed using Spearman's rank correlation, validated five critical delay factors impeding AI implementation: absence of a coherent strategy, challenges in talent acquisition, entrenched functional silos, limited managerial commitment, and resistance to behavioural change. These factors collectively contribute to delays in machine learning and AI project execution across the pharmaceutical landscape. The authors identified an opportunity for the convergence of ML to advance into NLP-based AI solutions. This allows decision-making similar to the human brain. The growth of the segment is expected to accelerate in the next 10 years. These developments might lead to the elimination of redundant roles in the pharmaceutical industry. Organisations can reassess long-term workforce planning of operational areas for AI adoption. The highest ROI is achieved by implementing ML and AI in operations, quality, supply chain, and engineering/maintenance. The operation segment has the least regulatory risk and can be used as the starting point for AI and ML integration in the pharmaceutical industry.

Using a meta-analysis of 10 papers, Taha (2025) noted that Artificial Neural Networks (ANNs) exhibit strong generalisation capabilities across large-scale datasets, rendering them effective for complex health prediction tasks. Nonetheless, limitations in interpretability and sensitivity to class imbalance remain persistent challenges. Autoencoders are well-suited for unsupervised pattern recognition and anomaly detection, yet their performance can degrade when handling heterogeneous data unless carefully tuned. Convolutional Neural Networks (CNNs) are particularly adept at processing spatially structured inputs, such as those encountered in radio genomics, but they demand significant computational resources and are prone to overfitting, especially with limited training data. Gradient Boosting Decision Trees (GBDTs) consistently deliver high predictive accuracy and are proficient at modelling non-linear relationships in medical datasets. However, their computational intensity necessitates regularisation strategies to prevent overfitting. K-Nearest Neighbours (KNN) offers intuitive clustering and pattern recognition capabilities, making it valuable for personalised medicine applications; yet its scalability is hindered by substantial memory and processing requirements in large datasets. Naïve Bayes (NB) classifiers are computationally efficient and easily interpretable, but their reliance on the assumption of feature independence often undermines predictive performance in complex biomedical contexts. Support Vector Machines (SVMs), while advantageous for high-dimensional data and rare disease classification, can become computationally burdensome when kernel methods are employed.

A focus group of 12 to 15 experts by Joshi, et al. (2022) showed that several key implementation challenges persist across tactical, operational, and strategic domains. The findings enhance understanding of the multifaceted barriers surrounding AI governance, scalability, and privacy, offering actionable insights for decision-makers. These obstacles stem from the broad spectrum of system-level, legal, technical, and operational considerations, compounded by the expansive deployment of AI technologies within public healthcare settings. The study used MCDM techniques to structure the multiple-level analysis of the AI implementation. Use of a single country and participants only from government hospitals are the limitations of this study. The authors suggest more empirical studies (case studies) collaboratively in many countries for comparison. The objectives of this study were to investigate the implementation barriers of AI in public healthcare in developing countries, viz., the Indian context, to understand the linkage barriers and the dependent, driving, and autonomous barriers among the selected barriers derived from the systematic literature review (SLR), and to

provide strategic recommendations to smooth the AI implementation in the public health systems.
The study by Hummel, et al. (2024) aimed to identify the evidence on the perspectives of patients and clinicians on big data applications in the clinic. The authors used semi-structured interviews and focus groups. To explore patient perspectives, 24 cancer patients of the Women's Hospital, along with 16 volunteers who are not currently seeking care, were interviewed. To explore clinician perspectives, 15 interviews were conducted in the Women's Hospital Erlangen. Interviewees expected and demanded that the data processing should match patient preferences and that data are effectively used to generate social value. The main result is the shared tendency of clinicians and patients to maintain individualistic ascriptions of responsibility for clinical outcomes. As the views were gathered as reactions to the inputs, cases, and interview guides, the findings have limited generalisability. Clustering does not mean statistical significance. The specificities of a single country, a women's hospital and cancer patients also limit generalisability. The authors suggested that the tendency to maintain individualistic ascriptions of responsibility for clinical outcomes needs to be supported with systemic governance and stakeholder alignment of expectations in data-intensive health settings and other domains related to health-related inferences.
To rigorously examine AI integration in health data protection, a mixed-methods approach was employed by Hossain, Mahabub, and Das (2024), combining empirical analysis, expert insights, and system-level evaluation. The study includes systematic data collection to identify trends and impacts of AI adoption, supplemented by semi-structured interviews with 20–25 stakeholders across federal and state agencies, public health, healthcare IT, cybersecurity, policy, and data governance. The case study method offers practical insights into real-world public health systems that leverage AI and integrated data frameworks, thereby validating both quantitative and qualitative findings. Secondary data sources include publicly available reports such as cybersecurity incident databases (e.g., HHS breach portal), public health records, and peer-reviewed literature covering metrics like breach rates (pre- and post-AI implementation), response times, compliance scores (HIPAA/state-level), and interoperability (measured via data exchange success rates). AI and data integration offer transformative potential for US digital health security, enabling proactive threat detection and automated compliance monitoring that reduces administrative burden. Real-time response and unified communication platforms enhance system-wide resilience. However, challenges persist: data silos hinder integration, algorithmic bias threatens equitable protection, and resource constraints limit smaller providers' capacity. Cross-sector collaboration is essential to building a robust and fair data protection ecosystem.
The authors highlight limitations of current AI applications and propose future research directions, including blockchain-based decentralised data management, quantum-resistant encryption, real-time threat intelligence platforms, and edge-deployed AI algorithms. Policymakers are urged to establish standardised frameworks for AI deployment and data integration.
To analyse the business models of AI-based CDSS on the market and to allow for generic statements on the design and state of the art of such business models, and thus, maximising the utility of this technology by providing a future business model Radić, et al. (2022) conducted a market analysis of AI-based solutions in the healthcare domain, identified a sample of 36 commercially available CDSS and analysed their business models using the theoretical business model concept by Gassmann et al. The authors

identified generic attributes and alternative conditions of CDSS business models on the market in the respective key business model elements' value proposition, value creation and value capture. Based on the findings, the authors proposed a business model framework for AI-based CDSS that gives a first overview of the design of business models in this new technology field. The limitations include AI systems' availability limitations of the company websites only in English and German, the desktop research method, and the possible limitations of definitions and attributes in the business models.

In a survey of 153 individuals from the Indian healthcare sector and a secondary thematic analysis, 43.79% of the individuals supported DL, 56.86% supported the treatment prediction ability of AI, and 37.9% of the individuals supported AI over traditional medications. The independent variables ML, DL, NLP, and RES (Rule-based Expert Systems) have a strong positive correlation with improving food quality. The authors suggested that the use of ML can potentially minimise production ambiguity, leading to better service delivery, greater profits, and lower waste and carbon emissions. During online counselling, the security and data protection level can be enhanced to increase the number of satisfied patients (UmaMaheswaran, et al., 2022).

Cho and Hong (2023) aimed to explore how machine learning technologies can improve healthcare operations management. Based on malaria microscopy image data from the NIH National Library of Medicine, a total of 24,958 images were used for deep learning training, and 2600 images were selected for final testing of the proposed diagnostic architecture. The empirical results indicate that the CNN diagnostic model correctly classified most malaria-infected and non-infected cases with minimal misclassification, with performance metrics of precision (0.97), recall (0.99), and f1-score (0.98) for uninfected cells, and precision (0.99), recall (0.97), and f1-score (0.98) for parasite cells. The CNN diagnostic solution rapidly processed a large number of cases with a highly reliable accuracy of 97.81%. The performance of this CNN model was further validated through the k-fold cross-validation test. These results suggest the advantage of machine learning-based diagnostic methods over conventional manual diagnostic methods in improving healthcare operational capabilities in terms of diagnostic quality, processing costs, lead time, and productivity. In addition, a machine learning diagnosis system is more likely to enhance the financial profitability of healthcare operations by reducing the risk of unnecessary medical disputes related to diagnostic errors. The limitations include the disadvantages of CNN, selecting only one ML, and problems of timely access to large datasets of high quality. Recommendations for future research include ethical research on technological singularity issues and developing more practical approaches to using AI and ML in healthcare.

Park, Kim, Jeon, and Kim (2024) tested the feasibility of predicting the closure of medical and dental clinics (MCs and DCs, respectively) and investigated important factors associated with their closure using ML techniques. Of the total 33164 good medical clinics, the authors selected 30687 operating and 996 closed medical clinics. Of the total 18134 good dental clinics, the authors selected 17691 operating and 443 closed dental clinics. Support Vector Machine (SVM) emerged as the best-fit model for predicting the closure of Medical Centres (MCs) based on cross-validation results (AUC 0.762; 95% CI: 0.746–0.777; P<.001), followed by Random Forest (RF) (AUC 0.736; 95% CI: 0.720–0.752; P<.001). For Dental Clinics (DCs), Extreme Gradient Boosting (XGBoost) performed best (AUC 0.700; 95% CI: 0.675–0.725; P<.001), with RF as the next best model (AUC 0.687; 95% CI: 0.661–0.712; P<.001). Key predictors of Medical Centre (MC) closures included years of operation, population growth, overall population size, and the proportion of medical specialities. In contrast, Dental Clinic (DC) closures were primarily driven by patient volume, annual fluctuations in patient numbers, years of operation, and the percentage of dental specialists. This study has several limitations. Although based on a two-year national dataset, the number of clinic closures during the study period was relatively small. Predictions were derived from aggregated data by matching operating clinics with closed ones, which may have led to the loss of nuanced information. Financial variables were not included. Additionally, the study design focused on closed clinics, with operating clinics selected at a 1:2 ratio using locality-based logistic regression propensity scores, raising concerns about under-sampling and potential overfitting. While the study period overlapped with the COVID-19 pandemic, this contextual factor was not accounted for. The analysis was limited to the Korean healthcare system. The authors recommended some research for the future based on the limitations of this study.

To establish a research model of artificial intelligence, green supply chain management practice, industry competition and sustainable development performance of the public healthcare supply chain, Chen, Long, Dong, Li, and Mao (2025) surveyed 301 Chinese listed pharmaceutical enterprises. The results showed that: (1) Artificial intelligence has a significant positive impact on the sustainable development performance of public healthcare supply chain; (2) Artificial intelligence has a positive impact on green supply chain management practice; (3) Green supply chain management practice has a positive impact on the sustainable development performance of public healthcare supply chain; (4) Green supply chain management practices play an intermediary role in the effect of artificial intelligence on the sustainable development performance of public healthcare supply chain, that is, artificial intelligence improves the sustainable development performance of supply chain through green supply chain management practices; (5) Industry competition actively regulates the impact of artificial intelligence on the sustainable development performance of public healthcare supply chain. The limitations are the inadequacies of surveys and ignoring factors other than industry competition. The authors suggested some future research areas.

A survey of 376 healthcare consumers was conducted by Singh (2022) to empirically examine the drivers and barriers to the adoption of Generative AI (GenAI) in personalised healthcare from the perspective of healthcare consumers. Linear Discriminant Analysis (LDA) emerged as the top-performing model, achieving an accuracy of 95.09%, an AUC of 99.68%, and a rapid execution time of 0.038 seconds. The study identified significant correlations between key variables and GenAI adoption, with the Digital Divide showing the strongest negative association ($r = -0.1235$). Feature importance analysis from the LDA model highlighted Understanding and Trust in AI Systems, Convenience and Accessibility, and Improved Health Outcomes as primary drivers of adoption. Consistent with these findings, both Logistic Regression and Random Forest models identified the Digital Divide as a persistent barrier to GenAI-based healthcare adoption. A probabilistic ordered regression further clarified the influence of these variables, revealing that 89.26% of the variance in adoption willingness was explained by the model. Digital Divide, Convenience and Accessibility, and Understanding and Trust in AI Systems were statistically significant predictors. The Limitations of convenience sampling and the inability of ML methods to capture dynamic attitudes, beliefs, and personal experiences of individuals regarding GenAI in healthcare are identified. Many recommendations for future research and practice on varied aspects of AI related to the topic have been given.

A survey of 70 healthcare experts by Whig, et al. (2022) showed that the adoption of AI technology has significantly enhanced operational efficiency in the healthcare sector, enabling simultaneous management of diverse patient needs. By addressing longstanding challenges, AI offers transformative solutions that could reshape the future of healthcare delivery. Its ability to detect complex diseases at early stages facilitates timely intervention and improves treatment outcomes, ultimately contributing to life-saving diagnostics. Advanced AI systems have also reduced the time and effort required by healthcare professionals, streamlining workflows and improving service delivery. Experts increasingly view AI as a key driver of growth in the healthcare industry, with the potential to accelerate innovation through the deployment of high-tech medical tools and intelligent systems designed to benefit humanity.

Discussion

The papers are synthesised using some numerical trends and the findings.

Numerical trends

Year of publication

The year-wise distribution of the 20 reviewed papers is presented in Table 1.

Table 1

Year of publication

Year	#
2021	1
2022	6
2023	3
2024	6
2025	4

Out of 20, 10 each were published during 2021-2023 (with only one paper in 2021) and 2024-2025. Thus, the publication of papers related to AI in healthcare accelerated beyond 2021.

Country of study

The country of study pattern regarding the 20 papers reviewed is shown in Table 2.

Table 2

Country of study

Country	#
NA	5
India	5
Jordan	1
USA	3
UAE	1
Germany	2
Korea	1
China	1
UK?	1

The first five papers were reviews. Hence, there was no question of a country of study (denoted as NA in the table). Indian studies dominated empirical studies with five papers, followed by the USA with three papers. There were two papers from Germany. One paper each was from Jordan, UAE, Korea and China. One paper (Whig et al., 2022) mentioned the UK, but it was not clear whether the samples were drawn from this country.

Method of study

Table 3 shows the methodology followed by the reviewed papers.

Table 3

Method of study

Method	#
Qualitative review	4
PRISMA Review	1
Survey	8
Meta-analysis	1
Focus group	2
Semi-structured interviews	1
Mixed approach	1
Market analysis	1
Secondary data analysis	2

Out of the five reviews, one used a PRISMA review and the remaining four used qualitative reviews. The remaining 15 papers used 16 methods, as one paper (Hummel et al., 2024) used both focus groups and interviews. Surveys, with eight papers, dominated among the methodologies used in empirical papers.

Mention of Limitations

As shown in Table 4, 10 papers mentioned limitations, and the remaining 10 did not mention any limitations. Seventeen limitations were mentioned by the 10 papers which mentioned them. Table 4 categorises these limitations.

Table 4

Mention of limitations

Limitations	#	Grand Total
NA	10	
Yes	10	20
Estimation Method	2	
Sampling	2	
Narrow focus	6	
AI applications	2	
Methodological	3	
Non-inclusion of some variables	2	17

A narrow focus on a single country or a certain aspect of AI applications was the main limitation. Six papers mentioned this. Methodological issues like the limitations of a cross-sectional survey were mentioned in three papers. Limitations of estimation methods, sampling (convenience sampling), AI applications tests and non-inclusion of certain variables were mentioned in two papers each.

Recommendations

As can be seen from Table 5, out of 20, five papers did not provide any recommendations. The distribution of the types of recommendations among the 15 papers is provided in Table 5.

Table 5

Recommendations

Recommendations	#	Grand Total
NA	5	
Yes	15	20
Research	5	16

Practice	7	
Research and practice	3	

Among the 15 papers, which provided recommendations, five papers limited their recommendations to research and seven to practice, and three papers included both research and practice in their recommendations.

Quality of paper

Based on the adequacies of each item in the Excel file, the approximate quality of the papers was rated on a scale of 0 to 5. The lowest score obtained was 3. Hence, Table 6 shows the quality distribution of the 20 reviewed papers in three categories.

Table 6

Quality of paper

Quality	**Category**	**#**
3 to 3.6	Low	4
3.7 to 4.3	Moderate	6
4.4 to 5.0	High	10

If we assume scores 3-3.6, 3.7 to 4.3 and 4.4 to 5.0 as low, moderate and high, respectively, the highest quality dominated with 10 (50%) of the papers reviewed. Fewer papers were in the moderate (6) and low (4) quality categories. Thus, overall, the quality of the reviewed papers trended to improve from low to high.

Synthesis of findings

The five review papers discussed the current and potential AI applications and their uses in the healthcare sector. Specifically, AI in healthcare is a disruptive process involving all stakeholders to ensure evidence-based and patient-centric care quality. Bajwa et al. (2021) predicted the short-medium-long term developments in AI and its applications in healthcare, alleging increasing complexity with increasing care requirements. Santamato et al. (2024) discussed how COVID helped to realise the value of AI in healthcare. AI-based methods accelerate drug discovery and development (Kandhare et al., 2025). Main challenges in using AI applications for healthcare are related to data quality, privacy and ethical concerns. Arowoogun et al. (2024) discussed how these challenges can be addressed. Zuhair et al. (2024) pointed out how AI enhanced the efficiency of healthcare processes, especially in developing countries.

The empirical studies used surveys, interviews, focus groups and mixed approaches to note the key factors shaping the transformative role of AI and ML in healthcare sector (Mohan et al., 2023), modest impact of AI on healthcare and quality compromises in developing countries (Al-Dmour et al., 2025), the growing preference for deep learning methods in the NHS, UK for administrative and data science functions (Chakravarthi et al., 2022), the role of AI in the management of healthcare systems (Pazhayattil & Konyu-Fogel, 2023), uses and limitations of ML methods in healthcare (Taha, 2025), implementation challenges (Joshi et al., 2022), the need to place the patient's interests first when using AI applications (Hummel et al., 2024), the usefulness of AI for the US digital health security (Hossain et al., 2024), the relative merits and demerits of various CDSS (clinical decision-supporting systems) (Radic et al., 2022), preference for AI to traditional healthcare systems and ensuring food quality (Umamaheswaran et al., 2022), usefulness of CNN for diagnosis (Cho & Hong, 2023), various ML methods to predict closure of dental clinics (Park et al., 2024), role of AI in ensuring sustainable healthcare practices via green supply chains (Chen et al., 2025), use of AI to quantify healthcare consumers' perspectives (Singh, 2022), and AI as a growth engine for healthcare sector (Whig et al., 2022).

Thus, the reviewed 20 papers provide a comprehensive picture of AI, its applications, usefulness, barriers and challenges to address and impact on evidence-based personalised healthcare quality.

Conclusions

This paper aimed to evaluate the status of research on AI in relation to healthcare. Overall, the review provided a comprehensive picture of AI, its applications, usefulness, barriers and challenges to address and impact on evidence-based personalised healthcare quality. Five reviews discussed the status and potential of AI in healthcare. They also discussed the challenges and solutions to them. The role played by AI in managing COVID, especially in developing countries, is notable. India dominated among the countries of the study; empirical studies used various methods like surveys, interviews, focus groups and mixed approaches. Methodological limitations of various types were noted as limitations in most papers. Most papers provided recommendations either for research or for practice, and rarely both. The 20 reviewed papers were mostly medium to high quality.

Limitations

Apart from the selected databases, others might have provided more papers useful for this review, as 20 may be a very low number for generalisations, especially of numerical trends. Setting the period from 2020 to 2025 might have excluded some good papers earlier than 2020. Meta-analysis could not be done on empirical studies due to the differences in variables and units of expression. Limitations of papers reviewed may reduce their generalisability.

Recommendations

Research

Future studies should have a wider focus, more generalisable sampling methods, an adequate sample size for valid conclusions (two papers had less than 200 as the sample size) and preferably use mixed approaches for a sufficiently deep understanding of the phenomenon being studied. Many more empirical studies, mainly as multiple case studies, across developed and developing countries will be useful. There is an emerging research trend of AI capabilities similar to the human brain. More research may be needed before this type of AI implementation in healthcare.

Practice

Some pilot studies should be done before implementing or scaling up by comparing AI applications for their possible uses in the healthcare sector across many countries. Many governments do not have policies and strategies to support AI implementation in their healthcare systems. This situation needs to be rectified. Absence of standards for AI practices in healthcare needs to be addressed by convening stakeholder meetings at various sub-global levels to converge into global standards. It should be imperative for all nations to implement these standards.

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