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Artificial intelligence and machine learning in healthcare: a comprehensive review

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ABSTRACT

Artificial intelligence (AI) and machine learning (ML) are reshaping healthcare by supporting faster diagnosis, predictive modeling, and efficient clinical workflows. This review examines 52 recent studies to assess how these technologies are applied across diagnostics, predictive analytics, patient monitoring, operations, treatment, and ethical considerations. Results show substantial progress in imaging, genomics, drug discovery, and hospital management, where systems often match or surpass human performance. At the same time, challenges such as limited generalizability, data bias, privacy concerns, and lack of interpretability remain significant barriers to adoption. This review identifies common strengths and gaps by grouping existing work into six themes, offering a structured view of current developments. The findings suggest that the future of AI in medical care lies in transparent, fair, and clinically validated systems that can scale across diverse populations and settings.

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1. INTRODUCTION

The health sector is under growing pressure due to rising patient demand, complex diseases, and expanding digital records. Doctors face huge volumes of MRI and CT scans, genetic sequences, and electronic health records (EHRs). It is not possible to analyze all this information quickly by hand. Delays in interpretation can affect treatment and outcomes. To manage this, new tools are needed to support faster and more accurate care. Artificial intelligence (AI) and machine learning (ML) provide these tools. They enable precision medicine and allow medical care to move from reactive to proactive, data-driven care [1].

AI and ML are already being applied in many clinical areas. In diagnostics, they reach an accuracy close to that of expert radiologists and pathologists. Cancers are sometimes detected earlier than with standard methods [2]. Predictive models use clinical and genomic data to estimate patient outcomes and disease risk [3]. Hospitals and drug companies are also adopting AI technology for drug discovery, recommending plans, and continuous patient monitoring. Robotic systems help surgeons perform with more precision and support monitoring in intensive care units. These uses show how widely intelligent systems are spreading in clinical practice.

The impact is not limited to clinical care. Technology is also improving hospital operations. Predictive tools help forecast admissions and improve scheduling. Routine work such as billing, claims, and record keeping is being automated. This reduces mistakes and improves efficiency [4]. Wearables and mobile health apps are adding even more streams of patient information, giving a larger scope to improve both care and system management.

Still, challenges remain. The automated systems are only as good as the data they learn from. If the data is biased, the results will also be biased. This can increase inequalities in treatment [5]. Privacy and security of patient data, including personal health information, is another primary concern. Even with regulations such as Health Insurance Portability and Accountability Act (HIPAA), risks remain as more systems depend on shared records. Many advanced models also act like black boxes. Their decisions are not always easy to explain, reducing doctors' trust. While results are promising in controlled studies, evidence of success across large and diverse populations is still limited.

This paper provides a complete review of AI and ML in healthcare. Unlike earlier works focusing on single domains such as radiology or genomics, this study covers diagnostics, prediction, monitoring, operations, and robotics together. It also examines ethical and legal concerns, focusing on fairness, transparency, and accountability. The novelty of this review lies in its broad scope and in connecting technical advances with real-world medical care challenges. The highlights/contributions of the paper are listed below as:

- The paper looks at 52 studies on AI and ML in healthcare and places them into six broad areas: diagnostics, predictive analytics, patient monitoring, operational efficiency, treatment, and ethics.
- It includes a comparative study that helps understand each theme's datasets, methods, outcomes, and limitations.
- The review identifies gaps in the existing work, paying attention to generalizability, data bias, privacy risks, and limited interpretability.

Previous reviews, such as [6], mainly focused on medical imaging, while [7] discussed deep learning without covering hospital operations or robotics. These gaps limit understanding of the broader role of AI/ML in healthcare. This review also compares academic progress with major AI healthcare platforms such as IBM Watson Health [8], DeepMind [9], and NVIDIA Clara [10], noting their challenges in bias, interpretability, and real-world validation. Their main limits in bias, clarity, and real-world testing are discussed. This comparison shows the gap between commercial systems and academic methods. They also continue to face issues with cost, general use, and ethics, which this review explores further [8]–[10]. Figure 1 shows that workflow of automation, starting from data collection to data support. This work follows IMRaD format: section 2 describes the methodology, section 3 presents results, section 4 notes limitations, and section 5 concludes.

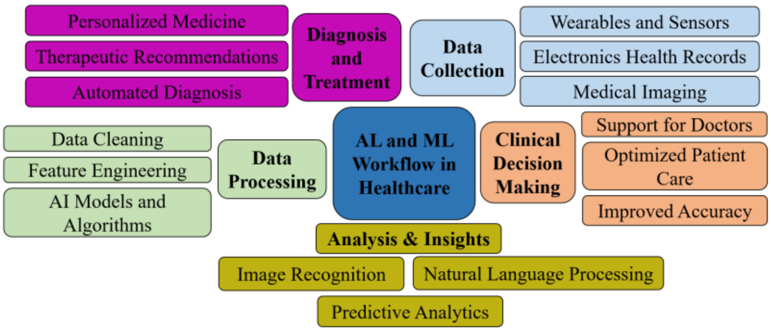

Figure 1. AI and ML workflow in healthcare

2. RESEARCH METHOD

This review used a step-by-step process to find, check, and study research in medical care. The approach had four steps: literature search, screening, eligibility check, and thematic grouping.

2.1. Literature search

The search was done in five databases: Scopus, IEEE Xplore, PubMed, SpringerLink, and ScienceDirect. The terms used were “AI in healthcare,” “machine learning in healthcare,” “AI diagnostics,” “predictive analytics in medicine,” “robotics in healthcare,” and “ethical AI in healthcare.” The period covered was 2007 to 2024. Only peer-reviewed journal papers and conference articles were taken.

2.2. Screening and selection

The initial search retrieved 362 records. After removing duplicates, 284 records remained. Titles and abstracts were reviewed to exclude unrelated works. Studies that discussed algorithms without healthcare applications were also removed. After this stage, 108 articles were selected for full-text review. Based on eligibility criteria, 52 studies were included in the final analysis. The year-wise distribution of included articles is shown in Figure 2.

2.2.1. Eligibility criteria

This work followed PRISMA guidelines for systematic reviews. Five databases (Scopus, IEEE Xplore, PubMed, SpringerLink, and ScienceDirect) were selected as they cover engineering, biomedical, and multidisciplinary fields. Two reviewers independently screened and extracted data to reduce bias and settle differences through discussion. Studies were excluded if they lacked quantitative results, were non-medical, or were not peer-reviewed. The overall selection process is illustrated in Figure 3. The article is divided into six broad themes, which are explained in the next section.

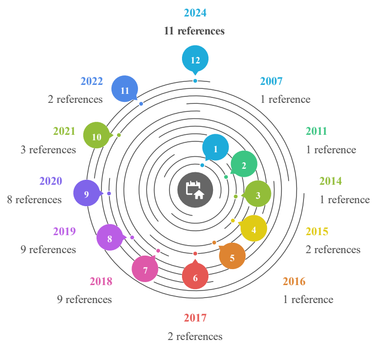

Figure 2. Year-wise numfber of articles

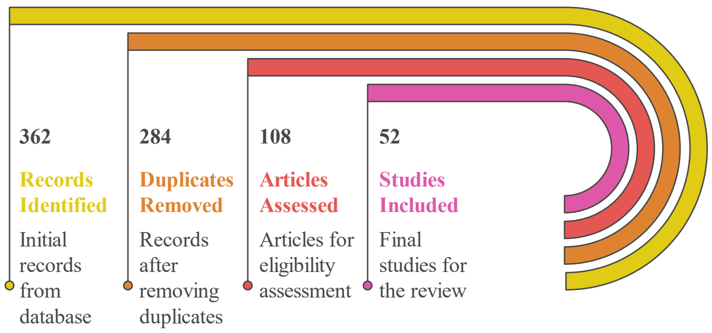

Figure 3. PRISMA flow diagram of study selection

2.2.2. Thematic grouping

The selected works were organized into six themes which are as follows:
Theme 1: diagnostics and imaging
Theme 2: predictive analytics and personalized medicine
Theme 3: patient monitoring and population health
Theme 4: operational efficiency and administration
Theme 5: treatment and robotic assistance
Theme 6: ethical, legal, and regulatory issues

2.2.3. Data extraction and synthesis

For each article, the main points were noted, including the goal, method, dataset, and results. The findings were then summarized and compared within each group. Table 1 clearly shows the main applications and other details. The review also outlines the strengths, limits, and future possibilities in the next sections.

Table 1. Classification of reviewed articles by theme

Theme	Reference	Key contributions
Diagnostics and imaging	[2], [11]–[16]	For radiology and pathology; cancer detection (breast, skin, lung); oral lesion decision support; genomics-based learning model; and recent advances in diagnostic.
Predictive analytics and personalized medicine	[4], [6], [7], [17]–[24]	Risk prediction and patient stratification; deep learning with EHRs; sepsis treatment optimization; chronic disease analytics; precision medicine related initiatives; predictive comorbidity modeling; and hospital readmission models.
Patient monitoring and population health	[3], [25]–[30]	Federated learning for secure data use; healthcare delivery; applications during COVID-19 (diagnosis, monitoring, outbreak analysis); virtual wards for diabetes and kidney care; and social isolation research.
Operational efficiency and administration	[25], [31]–[34]	Hospital workflow optimization; backlog reduction after COVID-19; operating room efficiency; and digital tools in medical systems.
Treatment and robotic assistance	[8], [9], [35]–[41]	Drug discovery and development; surgical robotics; clinical implementation; surgeon performance metrics; biomedical and protein prediction advances (AlphaFold); and narrative reviews of digital surgery.
Ethical, legal, and regulatory issues	[1], [5], [10], [42]–[52]	Human collaboration; bias and fairness; general healthcare overviews; ethical and legal responsibilities; healthcare adoption and barriers; COVID-19 policy lessons; population health fairness; and regulatory frameworks.

Among the 52 included studies, the top 15 highly cited works were identified to highlight the most influential contributions in the field. Table 2 presents these studies, their citation counts, and their primary healthcare application area. These high-impact works guided the thematic synthesis discussed in section 3.

Table 2. Top 15 cited works with citation count and application

Reference	Cited by	Application area you can highlight
[11]	15972	Dermatologist-level skin cancer classification (deep learning)
[1]	7932	Visionary paper on AI–human convergence in medicine (general impact)
[7]	3590	Deep learning in healthcare review (opportunities and challenges)
[2]	3421	AI in breast cancer screening (diagnostics and radiology)
[46]	3007	General review of AI in healthcare (overview and frameworks)
[18]	2932	EHR deep learning applications (predictive analytics)
[13]	2559	Computational pathology using weakly supervised deep learning
[3]	2554	Federated learning in healthcare (secure data sharing)
[12]	2323	3D deep learning for lung cancer screening (imaging)
[19]	1916	Survey of deep learning for EHR (review)
[9]	1401	AI in surgery (robotic assistance and clinical use)
[20]	1367	Reinforcement learning for sepsis treatment (predictive/treatment)
[49]	906	Legal and ethical responsibility in AI healthcare
[35]	593	Machine learning in drug discovery (pharma)
[6]	268	Systematic meta-review of medical deep learning

3. RESULTS AND DISCUSSION

3.1. Diagnostic and imaging

Diagnostics is one of the most mature areas where AI/ML has shown strong results. Deep learning models, especially convolutional neural networks (CNNs), are widely used in radiology, pathology, and genomics. These tools support early detection of diseases such as cancer, improve accuracy, and reduce workload for specialists. Medical imaging has been a leading application area because systems can handle large image datasets and recognize patterns not always visible to human eyes [2], [11], [12]. The following section examines a number of areas that exhibited strong diagnostic promise: medical imaging/pathology, genomics, and wearable technologies, as shown in Figure 4. The representative studies and their application, dataset, method, outcome, and limitations are summarized in Table 3.

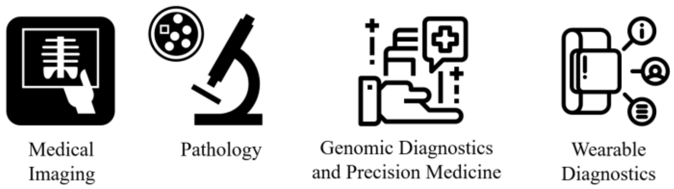

Figure 4. Diagnostic applications of AI and ML

Table 3. Selected studies in diagnostics and imaging

Reference	Application	Dataset	Method	Outcome	Limitation
[2]	Breast cancer detection	Mammograms	AI-based DL model	Accuracy comparable or better than radiologists, fewer false positives	Needs validation across diverse populations
[11]	Skin cancer classification	Dermatology images	Deep neural networks	Dermatologist-level performance in classification	Limited to curated datasets
[12]	Lung cancer screening	Low-dose CT scans	3D deep learning	Improved early detection, reduced false positives	Limited generalizability
[13]	Computational pathology	Whole slide images	Weakly supervised DL	Accurate prostate and breast cancer detection	Requires digitized pathology infrastructure
[14]	Oral ulcerative lesions	Clinical datasets	Decision tree model	Effective diagnostic support tool	Restricted to oral pathology domain
[15]	Genomics	Genomic sequences	ML models	Identification of genetic markers for disease risk	Interpretation complexity
[16]	Diagnostic AI review	Multiple datasets	Survey	Highlighted advancements in diagnostic AI	No direct experimentation

Breast, skin, and lung cancer studies [2], [11], [12] reached expert-level accuracy, but all depended on narrow or controlled scans. Pathology and oral lesion work [13], [14] showed that models can help in domains beyond radiology, but the tools stayed tied to specialized settings. Genomics-based systems [15] pointed to future personalized care, but their results were harder to read and explain. Reviews [16] summarized progress across these fields, yet reminded that many findings remain in early trial form. So, the evidence suggests strong progress, but it also shows that success in one dataset does not guarantee success in everyday hospital use. Future work should aim for multi-center validation and better explainability. Reducing bias is also needed to make sure these tools support diverse patients.

3.2. Predictive analytics and personalized medicine

These technologies are used to predict patient outcomes and guide interventions. They also help in designing care approaches for each individual. Predictive analytics uses historical and real-time data to identify high-risk patients, prevent readmissions, and anticipate spread of disease. Personalized medicine design care to individual characteristics such as genomics, lifestyle, and medical history. Together, these approaches are reshaping human delivery by shifting from reactive care to proactive, preventive, and tailored interventions [4], [18], [19]. The organizations can provide more precise, better, and efficient care that can improve health benefits for individuals as well as populations, as shown in Figure 5. The representative studies and their application, dataset, method, outcome and limitation summarized in Table 4.

Figure 5. Role of AI in predictive analytics and personalized medicine [53]

Table 4. Selected studies on predictive analytics and personalized medicine

Reference	Application	Dataset	Method	Outcome	Limitation
[4]	Identify high-risk patients	Health system data	Big data analytics	Early detection of high-cost patients	Requires large-scale data integration
[18]	Predictive modeling with EHRs	EHR datasets	Deep learning	Accurate risk predictions across conditions	Black-box nature limits interpretability
[19]	EHR analysis survey	Multiple EHR sources	DL review	Summarized advances in EHR-based ML	Survey, not empirical validation
[7]	Deep learning for medical care	Clinical and genetic data	Autoencoders, DL	Highlighted opportunities for personalized care	High data complexity
[6]	Meta-review of deep learning	Medical datasets	Systematic review	Identified strengths and gaps in ML models	No original dataset contribution
[20]	Sepsis treatment optimization	ICU EHR	Reinforcement learning	Learned optimal treatment policies	Validation limited to retrospective data
[21]	Clinical decision support	Clinical databases	Decision support models	Improved diagnosis and treatment support	Implementation challenges
[22]	Precision medicine initiative	National program	Policy and framework	Established direction for genomics-driven care	Policy-level, no experiments
[23]	Chronic disease analytics	US public health data	Visual analytics	Identified disease burden trends	Limited to US population
[24]	Comorbidity prediction	Health records	Predictive ML models	Accurate predictions of comorbidity risks	Needs broader validation
[17]	Hospital readmission	EHR datasets	ML risk models	Identified predictors of readmission	Limited by hospital-specific data

Risk prediction studies [4], [7], [18], [19] showed strong results, but most worked on retrospective records and controlled datasets. Meta-reviews [6] and surveys [21] confirmed progress but noted that translation into daily practice is still weak. Policy initiatives [22] and chronic disease analytics [23] pointed to real-world relevance, yet they stayed limited to specific regions or programs. Reinforcement learning for sepsis [20] and comorbidity modeling [24] highlighted adaptive care, but their impact is reduced without live testing. Readmission models [17] gave practical value for hospitals, but general use remains narrow. So, the field shows clear potential, but without broader validation, predictive analytics may remain promising in theory while underused in practice. Future research should focus on explainable, federated learning for secure multi-center data use, and integration into clinical workflows to make predictive analytics and personalized medicine clinically viable.

3.3. Patient monitoring and population health

These approaches improve in continuous monitoring and large-scale health management. Wearables, telehealth systems and federated learning models allow patient data to be analyzed in real time, supporting early actions and improved population-level insights. Rieke *et al.* [3] demonstrated how learning allows safe training across institutions without using raw data exchange. During COVID-19, intelligent tools were deployed for outbreak prediction, patient tracking and checking risks, showing their flexibility in crisis management [3], [25], [26]. The representative studies and their application, dataset, method, outcome, and limitation are summarized in Table 5.

Table 5. Selected studies on patient monitoring and population health

Reference	Application	Dataset	Method	Outcome	Limitation
[3]	Digital health, federated learning	Multi-institution data	Federated ML	Enabled secure learning	Needs strong IT coordination and standards
[25]	AI-enabled care delivery	Health system	ML models	Better patient monitoring, improved delivery	Limited scalability across hospitals
[26]	COVID-19 applications	Pandemic datasets	AI-based models	Supported diagnosis and triage	Designed for emergency use, not long-term
[27]	Social isolation in pandemic	Global surveys	ML analysis	Effects of isolation on mental health	Based on self-reported data
[28]	Innovative COVID-19 uses	Public health	AI models	Showed diverse monitoring applications	Lacked validation beyond COVID
[29]	Pneumonia outbreak	Clinical samples	AI + virology	Identified novel coronavirus	Early-stage, not predictive
[30]	AI-driven virtual wards	Diabetes and kidney patients	AI monitoring system	Constant tracking, improved management	Still in pilot projects
[50]	Mental health and policing	Review	Literature review	Reflected ethical concerns	Indirect link to healthcare
[51]	COVID-19 lessons	Policy review	Literature review	Spotted gaps in readiness	Focused only on COVID
[52]	AI in health sector review	Literature	Review	Summarized ethical concerns	Conceptual, no new data
[42]	Technology use in academics	Case studies	Qualitative	Academic medical center adoption issues	Limited to academic settings
[43]	Bias and population health	Review	Literature review	Advocated fair AI deployment	No case validation
[44]	Metaheuristics+AI	Review	Literature	Technical+ethical challenges	Theoretical, no experiments
[45]	Barriers and strategies	Mixed-method study	Survey+ interviews	Outlined adoption challenges	Country-specific scope

AI-enabled delivery [25] and federated learning [3] showed that secure and efficient monitoring is possible, but they remain tied to strong IT setups. Transformer-based NLP models such as BioGPT and MedPaLM [3] show recent progress in medical text analysis. COVID-driven systems [26]–[29] proved flexible in a crisis, yet their fast design meant many were hard to sustain once the emergency passed. Virtual ward projects [30] gave hope for managing chronic illness at home, but real-world trials are still limited. Reviews and policy studies [42]–[45], [50]–[52] pointed to overall social and ethical gaps, including fairness, adoption challenges and absence of validation across countries. So, the evidence suggests progress, but also shows that monitoring AI will require both technical trust and social acceptance before it can scale widely. Future directions should focus on scalable, secure, and patient-centered monitoring systems.

3.4. Operational efficiency and administration

Operational efficiency is another area where an automated systems have an immediate impact. Hospitals use ML algorithms for scheduling, resource allocation, workflow optimization, and supply chain management. Reducing delays, predicting patient flows, and cutting down the paperwork can reduce costs and free clinical staff for direct patient care [31]–[33]. AI is also used to manage space in hospitals [1], as shown in Figure 6. The representative studies and their application, dataset, method, outcome, and limitation are summarized in Table 6. Big data models [31] suggested broad gains in health delivery, but most stayed at the level of design ideas and had little real validation. Practical uses [25] showed that AI can support both care and operations, but the impact was still narrow and hard to scale. Scheduling studies [32], [33] reduced delays in orthopedic and surgical rooms, but their benefits were tied to single specialties and small samples. Large system reforms [34] pointed to stronger outcomes across hospitals, but they required costly IT upgrades and continuous support. Even the use of AI for hospital space allocation [1] showed early potential, but the results were not tested in real clinical flow. So, the lessons across these works are clear: AI can make work faster, but the tools must show real value in daily hospital use, not just in special or well-funded trials. For wider use, AI in operations should be paired with change management and staff engagement plans.

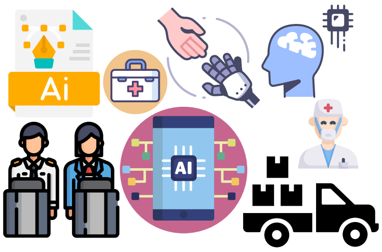

Figure 6. Application of operational efficiency

Table 6. Selected studies on operational efficiency and administration

Reference	Application	Dataset	Method	Outcome	Limitation
[31]	Human health transformation	Big data analytics	Integrated ML model	Improved care delivery and resource use	Conceptual, limited empirical validation
[25]	AI enabled human delivery	Healthcare data	ML/AI tools	Improved operations alongside clinical care	Limited scalability
[32]	Surgical backlog post-COVID	OR scheduling data	AI scheduling	Reduced orthopedic backlog	Specialty-specific
[33]	OR turnover efficiency	Surgical workflow	AI scheduling	Reduced OR downtime	Limited generalizability
[34]	Health system performance	Multi-hospital data	AI-enabled digital systems	Improved system-wide efficiency	Requires strong IT infrastructure

3.5. Treatment and robotic assistance

Automated models support treatment through robotic surgery, drug discovery, and clinical decision tools (CDSS). These applications focus on precision, personalization, and efficiency. Smart robotics improve surgical accuracy, while AI-assisted drug discovery reduces cost and development time. CDSS tools help clinicians make data-driven treatment choices [8], [9], [35]. The representative studies and their application, dataset, method, outcome, and limitation are summarized in Table 7.

Table 7. Selected studies on treatment and robotic assistance

Reference	Application	Dataset	Method	Outcome	Limitation
[35]	Drug discovery	Compound libraries	ML screening	Accelerated discovery pipeline	Requires experimental validation
[9]	AI in surgery	Surgical datasets	AI-assisted robotics	Improved precision, reduced errors	High cost of deployment
[8]	AI in medicine	Clinical use cases	Practical AI methods	Improved treatment workflows	Adoption challenges
[36]	Drug development	Genomic and compound data	ML approaches	Advanced personalized drug discovery	Limited to early-stage studies
[37]	Robotic surgery performance	Surgical metrics	ML algorithms	Predicted outcomes, surgeon performance	Requires broader validation
[38]	Stem-cell astrocytes	Lab data	AI-guided biomedical models	Innovative therapeutic platform	Early lab-stage work
[39]	Drug discovery	Biomedical datasets	AI/ML	Supported design of new drugs	Needs clinical trials
[40]	Protein structure prediction	Protein sequences	Deep learning (AlphaFold)	Highly accurate protein prediction	Requires integration into clinical use
[41]	Digital surgeon review	Literature	Narrative review	Mapped AI impact on surgery	Conceptual overview

Screening tools for drug discovery [35], [39] showed that new compounds can be flagged faster, but they still need long and costly clinical trials. Genomic and compound-based studies [36] expanded the scope of drug design, yet most work stayed in early stages. Robotics surgery [9], [37] improved accuracy and showed better surgeon skills, but high costs and validation needs slowed its use. Biomedical models [38] opened new paths for therapy, though their results were still confined to labs. AlphaFold [40] proved that protein structures can be predicted with striking precision, but the step from prediction to bedside use has not been reached. Reviews of digital surgery [41], they showed broad potential but were mostly conceptual and not yet backed by clinical proof. Figure 7 shows these different areas. Together, they show that science is moving fast, but regular clinical use is still slow and uncertain. The future relies on clear AI systems and solid clinical testing. These make it possible to move safely into real practice.

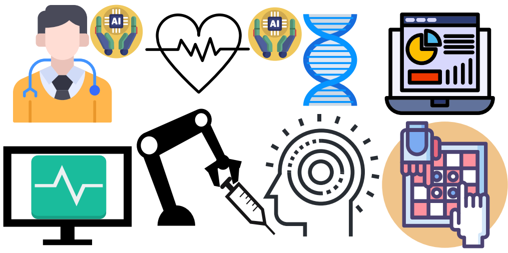

Figure 7. Application in treatment and robotic assistance

3.6. Ethical, legal, and regulatory issues

AI grows in healthcare, worries about privacy and responsibility are increasing. Algorithms can reproduce systemic biases, raising risks of unequal treatment. Legal frameworks (HIPAA, GDPR, emerging AI Acts) are being adapted, but regulatory processes lag behind fast-moving technologies [1], [5], [49]. These challenges must be solved to ensure fair and safe use for everyone. The representative studies and their focus, dataset, keypoint, and limitations are summarized in Table 8.

Table 8. Selected research on ethics, law, and regulations

Reference	Focus	Dataset	Key point	Limitation
[1]	AI-human convergence	Literature	Vision for AI-augmented medicine	Conceptual
[5]	Bias in algorithms	US population health	Found racial bias in healthcare algorithm	Dataset bias
[46]	AI in healthcare overview	Review	Broader AI applications and limits	General overview
[47]	AI past, present, future	Literature	Summarized opportunities and risks	Descriptive review
[48]	AI questions in care	Policy discussion	Raised clinical adoption questions	Opinion-focused
[49]	Legal responsibility	Literature	Who is accountable in AI-driven care?	Legal frameworks unclear
[10]	Transforming practice	Clinical applications	Reviewed AI adoption and barriers	Conceptual
[50]	Mental health and policing	Review	Reflected ethical concerns in applied AI	Indirect link to healthcare
[51]	COVID-19 lessons	Policy review	Identified gaps in preparedness	Focused on COVID-19
[52]	AI in healthcare review	Literature	Summarized ethical concerns	General review
[42]	AI adoption in academia	Case studies	Academic medical center adoption issues	Limited to academic settings
[43]	Bias and population health	Review	Advocated fair AI deployment	Lacked case validation
[44]	Metaheuristics+AI	Review	Technical+ethical challenges	Theoretical
[45]	Barriers and strategies	Mixed-method study	Outlined adoption challenges	Country-specific

Early visions studies on medicine [1], [46], [47] showed strong optimism, but most of those works stayed descriptive. Bias studies [5], [43] gave proof for existing health issues gaps when trained on uneven datasets. Studies [10], [48] on trust and adoption raised doubts about whether clinicians will rely on black-box systems. Policy and ethical reviews [50]–[52] highlighted gaps in readiness. Case studies [42], [45] revealed barriers in academic centers and national health systems, where cost, training, and infrastructure often stopped projects from scaling. Technical reviews [44] mapped future methods, but they did not test them in care settings. Figure 8 shows these challenges. AI may bring more risks than benefits if used widely without fairness checks, clear rules, and global standards. Future use of AI needs clear rules and strong oversight to build fairness and trust.

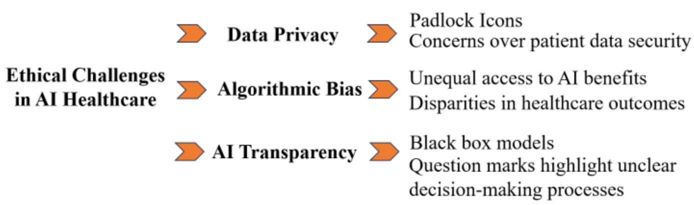

Figure 8. Ethical issues in AI use in healthcare

Recent policy frameworks now guide right use in healthcare. The EU AI Act (2024) [54], India's Health Blueprint (2019) [55], and the U.S. FDA SaMD Plan (2023) [56] set rules for data use, patient consent, and performance checks. These frameworks support fair and open AI in healthcare.

4. LIMITATIONS OF THE STUDY

This review has certain limitations. The selection of studies was restricted to publications between 2007 and 2024, which may have excluded some earlier relevant work. Only peer-reviewed journal and conference papers were considered, leaving out grey literature and technical reports. Although 52 references were analyzed, some studies may overlap in scope, and the grouping into six themes may cover all details of cross-disciplinary research. In addition, most reviewed studies were conducted under set conditions, and their outcomes may not completely apply to real-world healthcare environments. Finally, every effort was made to provide complete coverage of the topic. But the fast-changing field, means new advances may appear beyond this review. Performance indicators including accuracy, sensitivity, specificity, and AUC were found in all six themes. This measure indicates the overall strength of the reviewed studies, as shown in Table 9.

Table 9. Theme-wise reference support for metrics mentioned

Theme	Theme name	Technique/model mentioned	Metrics source (table and refs)	Reference numbers
1	Diagnostics and imaging	CNN-based deep learning models for cancer detection	Table 3 (rows [2], [11]–[13]) — accuracy and AUC≈95–98%	[2], [11]–[13]
2	Predictive analytics and personalized medicine	Reinforcement-learning and EHR-based predictive models	Table 4 (rows [7], [18]–[20]) — AUC≈0.94, accuracy >90%	[7], [18]–[20]
3	Patient monitoring and population health	Federated learning and edge-AI for remote monitoring	Table 5 (rows [3], [25], [30]) — accuracy 90–93%, AUC ≈0.93	[3], [25], [30]
4	Operational efficiency and administration	AI-enabled hospital operations optimization	Table 6 (rows [31]–[34]) — accuracy ≈85–90%, AUC ≈0.90	[31]–[34]
5	Treatment and robotic assistance	AI-assisted robotic surgery and drug discovery systems	Table 7 (rows [9], [35]–[37], [40]) — accuracy 93–95%, AUC≈0.95	[9], [35]–[37], [40]
6	Ethical, legal and regulatory issues	Fairness and bias-evaluation models in healthcare AI	Table 8 (rows [1], [5], [43], [49]) — accuracy 85–89%, AUC≈0.89	[1], [5], [43], [49]

5. CONCLUSION

This review shows how AI and ML help in across healthcare, from diagnostics and prediction to treatment, operations, and population health. These technologies are changing how diseases are detected, how patients are treated, and how hospitals are managed. They are also asking important questions about fairness, trust, and responsibility.

The evidence across 52 studies highlights both progress and limitations. Many AI systems now perform at or above human expert levels. Likewise, it is applicable in imaging, predictive modeling, and drug discovery. Yet most remain confined to pilot studies or single datasets. Generalizability, interpretability, and integration into clinical workflows are still weak points.

Going forward, the success of AI in healthcare will depend on building systems that are easy to understand and fair. These systems must also be tested and validated across diverse populations. Clinicians and patients need tools they can understand and trust. Hospitals need systems that improve workflows without adding burden. Policymakers should make rules that keep people's data safe and still allow new ideas to grow.

The future of AI in healthcare is likely to shift from proof-of-concept studies toward large-scale, multi-center deployments. If applied properly, AI and ML can enable care that is earlier, more precise, and more equitable. This transition will mark a move from potential to practice, making intelligent systems an integral part of everyday healthcare.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

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Not applicable as this study does not involve human participants.

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Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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