

MINI-REVIEW

Challenges in incorporating artificial intelligence into daily healthcare practice

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Abstract

Artificial intelligence (AI) holds huge potential in improving diagnosis and streamlining workflows in health care. However, several challenges remain, hampering the widespread adoption in clinical settings, such as for assessing data quality, bias, interoperability, and privacy, as well as for use in regulation and clinician training. Potent data channels are vital for assuring the exactness and trustworthiness of diagnostic performance. They boost the transmission of high-quality information, which is essential for expert annotations. Interoperable electronic health record integration and federated or privacy-enhancing training approaches allow real-time analytics while guarding patient data. Regulatory indecision and the comprehensive and continuous supervision of the process require transparent, explainable AI and shared accountability among developers, doctors, and institutions. In addition, prospective clinical validation, physician education, and governance are paramount to building trust and guaranteeing safe AI deployment in health care. This review outlines the difficulties faced when integrating these technological advancements into everyday clinical practice.

Keywords: Artificial intelligence; Health care; Data quality; Data security; Ethics; Regulatory compliance; Clinical validation

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1. Introduction

Artificial intelligence (AI) revolutionizes medical research and clinical practice through large data analysis, contributing to major scientific advancements.^{1,2} AI applications encompass multiple medical domains, such as early detection, diagnosis, precision medicine, and outcome prediction.^{3,4} AI displays promising potential, but challenges to its adoption, including data bias and category imbalances, as well as the need for comprehensive datasets and meticulous selection of training algorithms, must be overcome. Ethical, legal, and privacy concerns, along with opaque “black-box” models, demand transparency, explainable AI, robust governance, and regulatory oversight to preserve patient trust and safety. To unleash the full potential of AI in adoption, multi-stakeholder collaboration, rigorous clinical validation, clinician training, and standardized data and evaluation frameworks are essential. The current review examines the challenges encountered when integrating these technological advancements into routine clinical practice.

2. Key challenges

2.1. Data quality and bias

2.1.1. Data quality

Effective AI models depend on large amounts of high-quality, analyzed data. Credible deep learning (DL) models require important training data.⁵ Hasei *et al.*⁶ showed that high-quality expert annotations enhanced AI accuracy in osteosarcoma X-ray diagnosis, achieving 95.52% sensitivity and 96.21% specificity with annotated data. Focusing on data in AI development emphasizes the transformative effect of quality training data on diagnostics.⁶ Inconsistent or poor-quality data can damage model strength and generalization.⁷ Disordered data constrain high-precision DL models. Imperfections or unconventional methods in data collection can lead to biased results. Extensive training and verification datasets are needed to avoid prejudices when creating AI models.^{8,9}

We repeatedly face several challenges that can impact the quality of our investigations, especially when manipulating data. Missing data are a constant issue that can lead to biased results and reduced accuracy.^{10,11} Furthermore, mistakes resulting from errors in data assemblage or aggregation can misinform decision-making, emphasizing the importance of detailed checks in data handling.^{10,12,13} Discrepancies, such as conflicting information from varied sources or duplicate entries, can further exacerbate matters and create uncertainty.¹²⁻¹⁴ These challenges are expanded when datasets are biased, which affects a model's ability to generalize effectively.^{15,16} While assimilating distinctive data types, improper or noisy data can interfere with model performance, adding another layer of complexity.^{10,16} Guaranteeing reliable and trustworthy analytics by managing these issues is crucial.^{11,14,17}

Systematic evaluation of data using quality metrics and frameworks helps identify and quantify issues.^{12,13,16} Techniques such as imputation, deduplication, and error correction are widely used to improve data quality.^{11,12,15} Scalable systems and machine learning (ML) methods are being developed to automate quality checks and anomaly detection.^{11,18}

2.1.2. Bias

Training data can introduce biases in AI models, leading to biased treatment outcomes.¹⁹ Utilizing health data that lacks information about vulnerable groups can cause unfairness in health care.²⁰ Bias could influence clinical, managerial, and public policy decisions. Data collection are susceptible to bias, and institutional heterogeneity limits generalizability, highlighting the importance of

external validation.²¹⁻²³ In addition, clinical data are often institution-specific due to patient privacy concerns.²⁴⁻²⁶ Ethical risks, fairness, standardized policies, and interdisciplinary governance need to be addressed to limit these problems.^{19,27}

3. Integration into clinical workflows

3.1. Usability

Healthcare professionals need AI systems that are easy to use and fit smoothly into their daily routines.²⁸ AI tools with a simpler interface would help enhance physicians' confidence and satisfaction in using them,^{29,30} thus improving the work efficiency. Healthcare systems should be both simple and capable of generating parameters that improve patient outcomes.^{31,32} A critical attribute of healthcare technology is its ability to empower physicians in decision-making rather than exhausting energy and time in providing care for patients.³³⁻³⁵ Every AI tool introduced into clinical practice must be thoroughly tested and validated in real clinical settings before adoption.^{29,36}

3.2. Clinical integration and electronic health record (EHR) interoperability

Harmonizing AI with EHR is crucial for their compatibility.^{37,38} Doing so helps consolidate patient data from various sources, with a comprehensive and unified patient record. This compatibility helps healthcare providers make better decisions.³⁹⁻⁴¹ When using AI, physicians can analyze real-time data from EHRs, which can enhance patient outcomes and avoid errors.⁴² For example, in-hospital mortality and readmission rates can be predicted by AI models.⁴³ Precision medicine can be significantly enhanced by AI to improve clinical decisions.⁴²⁻⁴⁴ Large data can be analyzed to reach an accurate diagnosis and avoid anomalies that may be missed by physicians.⁴⁵ AI algorithms can predict acute conditions earlier than current best practices, enabling timely interventions to improve patient care. Managing chronic diseases and optimizing treatment can be enhanced using AI.^{46,47} Furthermore, safety can be improved with the use of AI by providing real-time alerts about potential medication errors, optimizing drug dosages, and reducing adverse drug reactions.⁴⁸

With AI technology, clinicians can spend more time on patient care.^{49,50} because AI-powered tools assist with performing various administrative functions such as data entry and appointment booking. Additionally, AI, together with DL functions, represents a crucial tool for analyzing genetic information and creating predictive models essential for precision medicine.^{51,52}

4. Data privacy and security

Adherence to healthcare regulations, such as the Health Insurance Portability and Accountability Act, is mandatory for the incorporation of AI with the EHR, and improving laws and regulations is necessary to avoid privacy violations.^{53,54} Maintaining data integrity and security through techniques such as blockchain can preserve privacy.^{55,56} Ethical fulfillment is important to avoid biases from unethical data practices.^{57,58} Multicenter information transfer agreements and distributed DL (DDL) can address data-sharing challenges with patient privacy protection. Integrating AI into daily practices requires meticulous data management, protection of patient information, and rigorous trust building in AI model usage. These steps are critical for the responsible use of AI and thus the improvement of patient care and outcomes.^{43,59,60}

Federated learning is a type of AI approach specifically created to address privacy concerns in data-driven applications. Instead of collecting all data in one place, federated learning allows multiple devices or organizations to collaboratively train AI models while keeping their raw data local and private.⁶¹⁻⁶³ Each participant (such as a hospital) trains the AI model using its own data. Only model updates (not the raw data) are sent to a central server for aggregation.⁶¹⁻⁶³ Sensitive information stays on the local device, minimizing the risk of privacy breaches, an approach that is different from the traditional centralized ML.^{61,63} Federated learning can be combined with privacy-enhancing techniques such as differential privacy, secure aggregation, and homomorphic encryption, to further protect individual data during model training and aggregation.⁶³⁻⁶⁶

Federated learning significantly reduces the risk of revealing personal or sensitive data, which is valuable in health care.⁶¹⁻⁶³ Despite its privacy advantages, federated learning is still vulnerable to specific attacks (such as inference or poisoning attacks) that can potentially spill information from model updates. Research efforts are needed to continuously strengthen these protections.^{64,67,68}

Cybersecurity threats can be detected proactively by AI, leading to an improvement in the security of EHR systems.⁵⁶ Using AI in daily practice can help to detect anomalies and problematic activities within the EHR system, such as unusual access patterns or unauthorized data modifications, which may indicate a cybersecurity breach.^{69,70} By reinforcing security measures, data integrity and confidentiality will be guaranteed, and this can be achieved using ML and DL models.^{69,70} These reinforcement measures are important for integrating AI into the EHR systems, enhancing physicians' confidence in the systems, and improving clinical efficiency, quality, and accuracy.^{29,30}

5. Regulatory and ethical considerations

Despite the rapid developments in the AI domain, the rules and regulations for governing their usage remain limited, causing uncertainty regarding the approval and utilization of AI tools in clinical settings.^{71,72} Obtaining regulatory approval is a significant challenge for the adoption of AI. Essential explanations of how the software operates are crucial for regulatory permission. In general, patient confidentiality, data security, and the transparency of AI systems are emphasized by these regulations.^{73,74} The U.S. Food and Drug Administration (FDA) is in the process of streamlining the AI approval processes by classifying AI tools as medical devices within a three-class risk system. AI devices fall mostly into the Class II and III categories.^{75,76} Manufacturers are required by the FDA to track these devices in real-life settings and to assess them, at both development and post-market phases.^{77,78} The responsible use of the new technologies needs clear regulations and ethical standards.

The ethical implementation of AI in healthcare necessitates addressing several key concerns. The most important part is to ensure privacy and data protection. Data are often confined to individual institutions, and merely removing personal identifiers may not be enough to prevent data breaches.^{79,80} To resolve these problems, DDL and multicenter information transfer agreements were developed.^{81,82} In addition, data bias must be addressed, as unethical data collection practices can introduce disparities that negatively impact different patient populations.⁸³ For ensuring proper utilization of AI tools, a clearly defined set of rules and guidelines should be established, and notable authorities should be appointed to govern their usage.^{82,84,85} To familiarize clinicians with the challenges in AI tools adoption, education and training sessions on AI capacities and limitations should be held.^{74,86}

6. Transparency and accountability

Transparency and clarity in the decision-making processes of AI systems are key to their trustworthiness and accountability. Thus, understanding how AI makes decisions is essential so that clinicians are proficient enough to review and verify all the proposed decisions.^{73,87}

6.1. The "black box" problem and explainability

Numerous AI models, specifically the DL systems, work as "black boxes," posing challenges in interpreting or verifying their decision-making techniques in clinical settings. Lack of clarity is the major factor that erodes trust of clinicians, contributing to hesitant adoption in clinics.⁸⁸⁻⁹⁰ Explainable AI (XAI) is envisioned as a solution, furnishing mechanisms for clinicians to comprehend, review, and

validate AI-generated instructions, thus supporting accountability and informed clinical decisions.⁸⁸⁻⁹¹

6.2. Accountability and shared responsibility

Traditional models of accountability are being challenged by AI, as clinicians often have limited control or understanding of AI-generated outputs. Thus, updated frameworks that include not only clinicians but also AI developers, safety engineers, and healthcare institutions in accountability structures are necessary.⁹²⁻⁹⁴ Evident guidelines and regulatory frameworks are required to define roles, responsibilities, and liability in cases of patient detriment or system collapse.⁹²⁻⁹⁵

6.3. Governance, regulation, and stakeholder involvement

Potent governance at both institutional and system levels is important for securing transparency, safety, and accountability. This includes regular audits, validation, and monitoring of AI systems.^{94,95} Involving all stakeholders, clinicians, patients, developers, and policymakers in the design, deployment, and oversight of AI systems is recommended to address ethical, legal, and practical concerns.^{94,96}

7. Clinical validation and trust

7.1. Validation

It is important to confirm the accuracy of AI models through clinical tests in real-world settings.^{97,98} These validations show how well the models perform, build physicians' confidence in the technology, and promote its daily use.⁹⁹ Without proper evaluation methods, the reliability of AI-driven predictions would remain doubtful and speculative.^{29,100}

7.2. Trust and collaboration

Collaboration between clinicians and data scientists is essential.¹⁰¹ To build trust between physicians and patients, AI developers should clarify the working principles of their systems or AI tools, as well as their benefits and weaknesses,¹⁰² enhancing physicians' confidence in them.¹⁰³ It is also essential to discuss issues such as patient consent, data privacy, and responsible use to create a supportive environment that leads to enhanced patient care and better results.¹⁰⁴ AI tools should be easy to use and fit smoothly into current workflows without causing disruptions.¹⁰⁴⁻¹⁰⁶

8. Training

Physicians need training on how to use AI tools to help them in their everyday work. Studies have shown that many physicians are not very familiar with AI, indicating

that they will not use these tools as much as they could in treating patients.^{107,108} Proper training can help physicians better understand how to apply AI, leading to better decisions and improved patient care. Sociotechnical factors can be fixed by training, ensuring that clinicians are knowledgeable about AI functionalities, which will increase their trust in these new technologies. Education is essential to maximize the benefits of AI in health care.¹⁰⁹⁻¹¹¹ Practical training for physicians on AI tools is essential to ensure safe, confident, and beneficial integration of AI into daily clinical practice. Structured education, practical experience, and ongoing support are needed. Physicians should understand what AI tools are, their capabilities, and their limitations,^{109,112,113} and they should be trained on how to evaluate when and whether to use a specific AI tool, including understanding its evidence base and potential biases.^{109,112,114} Hands-on instruction on how to operate AI tools in real clinical scenarios is crucial.^{109,115,116} Physicians must learn how to integrate AI outputs into their clinical reasoning.^{109,114,117} Training should include how to explain AI-assisted decisions to patients transparently.¹⁰⁹ Doctors need to recognize possible risks, such as over-reliance on AI or errors from algorithmic bias.^{109,114,117}

9. Access and equity

Ensuring fair access to AI technologies in low-resource settings is vital for improving global care. AI can help reduce healthcare disparities by enhancing diagnosis, treatment, and patient management, particularly in underserved areas with limited resources.¹¹⁸⁻¹²⁰

Successfully implementing AI in hospitals requires more than strong leadership or well-designed systems—it depends on clinician engagement and demonstrating clear, tangible value. When AI fails, it is often due to technical hiccups, organizational silos, or cultural resistance. To realize the full potential of AI in health care, we must tackle these challenges together through a holistic and inclusive approach. [Table 1](#) summarizes real-world case studies of AI implementation in hospitals, highlighting both successes and failures.

Different regions and regulatory bodies had different paths for AI and medical devices. In the US, Europe, and Asia, dissimilarities in approval timelines, safety, and data privacy can affect how quickly innovations reach patients. [Table 2](#) summarizes a comparison of these approaches.

9.1. Take-home messages and priorities for clinical practice

Take-home messages for best practice are as follows

- (i) Prioritize data quality: expert annotations markedly improve diagnostic accuracy.

Table 1. Examples of AI implementation in hospitals: outcomes and key factors

AI Application/Use case	Area of use	Outcome (success/failure)	References
UC San Diego Health, USA	Sepsis prediction (COMPOSER model)	Success: Sepsis mortality reduced by 17%	121
Multiple Dutch Hospitals, Netherlands	Radiology AI (various tools)	Mixed: Partial success	122,123
Large Norwegian Hospital Trust, Norway	Commercial AI for clinical workflow	Success: Enhanced digital maturity	124
Humber River Hospital, Canada	Hospital-wide digital transformation	Success: Improved efficiency	125
Multiple European Hospitals	Diagnosis, logistics, and rare diseases	Mixed: Varies by use case	126
US Health Systems (Survey)	Clinical documentation, radiology, and sepsis detection	Mixed: Documentation most successful	127
Chinese Tertiary Hospitals	Large language model (LLM) tools	Limited adoption	128

Table 2. Comparison of FDA, EMA/EU, and Asian regulatory approaches for AI and medical devices

Region/Agency	Regulatory focus & process	Key features and differences	References
USA (FDA)	Product-based, risk-classified approval (510(k), De Novo, PMA for devices, SaMD for AI)	Rigorous pre-market review, strong post-market surveillance, “total product lifecycle” for AI/ML, flexible for innovation, but slower approval	129,130
Europe (EMA/EU)	Notified bodies certify devices under MDR and IVDR; new EU AI Act for AI risk categories	Historically faster, less stringent pre-market review, but MDR/IVDR now impose stricter requirements; GDPR enforces strong data privacy; new AI Act aims for a global standard	131
Asia (e.g., China, Japan, and Korea)	Country-specific agencies (e.g., NMPA in China, PMDA in Japan); harmonization efforts via IMDRF	Varying rigor: Japan aligns with the EU/US, China is rapidly evolving with stricter data localization and privacy; less harmonized, often slower, and less transparent	132

Abbreviations: AI: Artificial intelligence; FDA: Food and Drug Administration; IMDRF: International Medical Device Regulators Forum; IVDR: *In Vitro* diagnostic regulation; MDR: Medical device regulation; ML: Machine learning; NMPA: National Medical Products Administration; PMA: Pre-market approval; PMDA: Pharmaceuticals and Medical Devices Agency; SaMD: Software as a Medical Device.

- (ii) Detect and mitigate bias early to preserve generalizability and fairness.
- (iii) Integrate AI into workflows with usable interfaces and EHR interoperability to improve adoption.
- (iv) Use federated learning and privacy techniques to protect patient data during model training.
- (v) Require explainability and clear accountability before clinical deployment.
- (vi) Conduct prospective clinical validation and clinician training to establish trust and ensure the safe use of the product.

Priority actions for clinical practice include the following:

- (i) Implement data quality pipelines and expertly label data.
- (ii) Adopt interoperable, workflow-embedded AI tools.
- (iii) Mandate explainability, monitoring, and governance.
- (iv) Train clinicians on technical use, decision integration, and patient communication.

10. Conclusion

To improve the use of AI in health care, we can consider a few key steps. Creating standardized guidelines for

collecting data and evaluating AI models to guarantee consistency and reliability in studies. Collaboration between physicians, data scientists, and regulatory bodies can help better integrate AI tools into the healthcare system, helping to establish confidence and transparency among healthcare providers. Together, these strategies can enhance the effectiveness and acceptance of AI in the healthcare system.

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Conflict of interest

The authors declare that they have no competing interests.

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