



# International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

**Operating Publisher**  
**SciFormat Publishing Inc.**  
ISNI: 0000 0005 1449 8214

2734 17 Avenue SW,  
Calgary, Alberta, T3E0A7,  
Canada  
+15878858911  
editorial-office@sciformat.ca

---

**ARTICLE TITLE**      ARTIFICIAL INTELLIGENCE IN MODERN MEDICINE:  
APPLICATIONS, CHALLENGES, AND ETHICAL CONSIDERATIONS

---

**DOI**                      [https://doi.org/10.31435/ijitss.1\(49\).2026.5242](https://doi.org/10.31435/ijitss.1(49).2026.5242)

---

**RECEIVED**            22 January 2026

---

**ACCEPTED**            14 March 2026

---

**PUBLISHED**         27 March 2026

---

**LICENSE**



The article is licensed under a **Creative Commons Attribution 4.0 International License**.

---

© The author(s) 2026.

This article is published as open access under the Creative Commons Attribution 4.0 International License (CC BY 4.0), allowing the author to retain copyright. The CC BY 4.0 License permits the content to be copied, adapted, displayed, distributed, republished, or reused for any purpose, including adaptation and commercial use, as long as proper attribution is provided.

# ARTIFICIAL INTELLIGENCE IN MODERN MEDICINE: APPLICATIONS, CHALLENGES, AND ETHICAL CONSIDERATIONS

**Gabriela Krok** (Corresponding Author, Email: gabrielakrok7@gmail.com)  
Henryk Klimontowicz Hospital in Gorlice, Gorlice, Poland  
ORCID ID: 0009-0000-3969-9929

**Anna Kulach**  
Medical University of Warsaw, Warsaw, Poland  
ORCID ID: 0009-0000-6476-8869

**Zofia Wcisło**  
Military Institute of Medicine, Warsaw, Poland  
ORCID ID: 0009-0009-9058-4882

**Karolina Lach**  
Medical University of Warsaw, Warsaw, Poland  
ORCID ID: 0000-0002-0529-1623

**Patrycja Piekarska**  
Medical University of Warsaw, Warsaw, Poland  
ORCID ID: 0009-0007-0085-6617

**Adrianna Purwin**  
Medical University of Warsaw, Warsaw, Poland  
ORCID ID: 0009-0008-5697-3721

**Grzegorz Szmit**  
Military Institute of Medicine, Warsaw, Poland  
ORCID ID: 0009-0000-5695-0388

**Maria Chmielewska**  
Mazovian Brodnowski Hospital, Warsaw, Poland  
ORCID ID: 0009-0002-7702-8282

**Weronika Basak**  
Military Institute of Medicine, Warsaw, Poland  
ORCID ID: 0009-0007-1788-3259

**Katarzyna Siwiec**  
Medical University of Warsaw, Warsaw, Poland  
ORCID ID: 0009-0001-6411-9727

**Łukasz Lamparski**  
National Medical Institute of the Ministry of the Interior and Administration, Warsaw, Poland  
ORCID ID: 0009-0005-3143-3583

**Wiktoria Modrzejewska**  
National Medical Institute of the Ministry of the Interior and Administration, Warsaw, Poland  
ORCID ID: 0009-0006-9165-7404

## ABSTRACT

Artificial Intelligence (AI) has rapidly emerged as a transformative force in modern medicine, offering significant advancements across diagnostics, treatment planning, patient care, and public health management. Recent innovations in machine learning, natural language processing, robotics, and data-driven decision support have enhanced accuracy, efficiency, and personalization in clinical practice. AI applications span numerous specialties, including radiology, pathology, emergency medicine, aesthetic medicine, and public health, with demonstrated benefits such as improved imaging interpretation, automated histopathological analysis, optimized triage, predictive modeling for disease prevention, and patient-centered treatment planning. Despite its potential, integrating AI into healthcare presents technical, organizational, and ethical challenges, including data quality limitations, algorithmic bias, transparency and interpretability issues, cybersecurity vulnerabilities, and regulatory complexities. Ethical concerns involve patient privacy, fairness, and the distribution of responsibility for AI-guided clinical decisions. Looking forward, the responsible deployment of AI will require continuous model monitoring, integration with clinical workflows, equitable training datasets, and collaborative oversight to ensure that AI complements healthcare professionals, promotes safety, and maximizes benefits for both individual patients and populations.

---

## KEYWORDS

AI in Medicine, Modern Medicine, AI-based Clinical Decision Support Systems, Healthcare Applications, Big Data in Medicine

---

## CITATION

Gabriela Krok, Anna Kułach, Zofia Wcisło, Karolina Lach, Patrycja Piekarska, Adrianna Purwin, Grzegorz Szmit, Maria Chmielewska, Weronika Basak, Katarzyna Siwiec, Łukasz Lamparski, Wiktoria Modrzejewska. (2026) Artificial Intelligence in Modern Medicine: Applications, Challenges, and Ethical Considerations. *International Journal of Innovative Technologies in Social Science*. 1(49). doi: 10.31435/ijitss.1(49).2026.5242

---

## COPYRIGHT

© **The author(s) 2026**. This article is published as open access under the **Creative Commons Attribution 4.0 International License (CC BY 4.0)**, allowing the author to retain copyright. The CC BY 4.0 License permits the content to be copied, adapted, displayed, distributed, republished, or reused for any purpose, including adaptation and commercial use, as long as proper attribution is provided.

---

## 1. Introduction

In recent years, AI has become one of the fastest-growing fields of science, with the number of publications in AI-related research increasing dramatically from the first uses in the 1960s to over 96 000 publications in diagnostics, 78 000 in drug development, 17 000 in cancer research, and 13 000 in pharmacology by October 2023, highlighting its rapidly expanding impact [1]. By incorporating machine learning, AI has transformed medical practice, enabling quicker and more precise diagnoses, tailored treatment plans, and streamlined handling of clinical data [2]. In medical practice, AI includes a range of computational methods that allow machines to recognize patterns, support clinical decision-making, learn from data, and process human language to assist in understanding and managing complex healthcare information [3]. However, as AI becomes more embedded in healthcare, it raises significant ethical concerns, including opaque decision-making, potential biases from historical data, and risks to patient privacy and equity [4]. The aim of this article is to review the current scientific literature on the applications, challenges, ethical considerations, and future prospects of AI in modern medicine.

## 2. Methodology of the Literature Review

The literature review was conducted using publications retrieved from electronic databases such as PubMed and Google Scholar. The search focused on peer-reviewed articles published between 2023 and 2025, addressing the applications, challenges, and ethical considerations of AI in medicine. The search was based on keywords: Artificial Intelligence, AI in Medicine, Medical Ethics, Clinical Applications, Public Health, AI in Radiology, AI in Emergency Medicine, Transparency, Algorithmic Bias, AI in Aesthetic Medicine, AI in Pathology.

### 3. Applications of AI in Modern Medicine

AI is increasingly being applied in medicine, offering innovative tools and technologies such as machine learning, natural language processing, rule-based systems, robotics and automation that support diagnosis, treatment, patient care and improve the efficiency of healthcare systems [5]. This chapter highlights key examples of AI applications across different areas of modern medicine.

#### 3.1 AI in Radiology

Modern radiology increasingly relies on AI, enabling more efficient and effective analysis of imaging studies. AI-driven systems, such as machine learning and natural language processing, automate routine tasks, facilitate early pathology detection, streamline diagnostic workflows, and enhance diagnostic capabilities, allowing radiologists to focus on more complex clinical cases [6]. These tools play a significant role across multiple areas of radiology, including neuroradiology, oncological imaging, thoracic diagnostics, cardiovascular evaluation, among others.

In neuroradiology, AI applications extend to both diagnostic imaging and interventional procedures. Digital subtraction angiography (DSA) plays a pivotal role in real-time interpretation of endovascular images, providing high-quality visualization of cerebral vessels and a reliable foundation for procedural planning and intraprocedural guidance [7]. Moreover, AI assists in detecting brain tumors, assessing neurodegenerative diseases, and diagnosing strokes and intracranial hemorrhages. These applications enable faster more accurate diagnostics, improved prognostic assessment of neurological disorders, and earlier initiation of potentially life-saving treatments. In oncological imaging, AI enhances the detection of breast tumors, which is particularly important given the rising incidence of this disease [6]. Initially, AI was most widely applied in mammographic screening, where it proved effective in identifying lesions [8]. For example, a breast cancer prediction algorithm trained on over 38,000 mammograms combined imaging data with electronic health records, enabling it to distinguish between normal and abnormal results and predict malignancy. Its performance is comparable to radiologists, with the potential to significantly reduce missed diagnoses [1]. In thoracic imaging, AI aids in evaluating chest X-rays, improving detection of pneumonia, pneumothorax, pleural effusion, and heart failure [6]. In the OPSCAN study, AI analyzed routine chest radiographs to identify individuals at high risk of osteoporosis. Among 40,658 participants, the AI model classified 4,912 (12.1%) as high risk, and these individuals were subsequently randomized. In the screening group, new-onset osteoporosis was diagnosed in 11.1% of patients compared with 1.1% in the control group (OR = 11.2;  $P < 0.001$ ). Among those who underwent the fully reimbursed DXA examination, 75.2% were diagnosed with osteoporosis. These findings indicate that AI-based analysis of chest X-rays can effectively support the identification of patients who require further bone density assessment [9]. In cardiovascular imaging, AI aids in identifying coronary artery disease, evaluating cardiac function, and detecting aortic aneurysms, contributing to more accurate assessments, tailored treatment strategies, and better patient outcomes [6]. Beyond diagnostic applications, AI and machine learning are increasingly applied in interventional procedures. For example, autonomous catheter navigation has been demonstrated using endoscopic sensors at the catheter tip to assist in paravalvular leak closure. Navigating the beating heart is particularly challenging due to continuous tissue motion and the opacity of blood, but machine learning algorithms can process the visual data from the endoscopic sensor to generate clear images of the catheter's point of contact and provide information on both the type of tissue encountered and force applied [10].

Effective implementation of AI in radiology requires access to advanced technologies as well as comprehensive training for medical professionals. Educating future clinicians is essential to ensure safe and effective use, thereby enhancing patient care and advancing modern radiology [8]. Radiology stands to benefit more than most medical specialties, as AI can take over time-consuming, repetitive, or technically challenging tasks. This will allow radiologists to dedicate more attention to interpreting findings in a clinical context, focusing on the analytical and intellectual aspects of their work that are central to the profession [11]. Recent studies have demonstrated that AI can significantly improve both the efficiency and accuracy of radiologists' work. For example, in a controlled study involving 111 radiologists assessing chest X-rays, the use of an AI-assisted system increased average diagnostic scores from 597 to 619 points and reduced the time needed to interpret 50 images from 3279 seconds to 1926 seconds. The greatest improvements were observed among intermediate and senior radiologists, with AI particularly supporting the detection of pathologies such as fibrosis, heart shadow enlargement, masses, pleural effusions, and pulmonary consolidation, highlighting its potential to streamline workflow while maintaining diagnostic quality [12].

### 3.2 AI in Pathology

Pathology is another field where AI is playing an increasingly important role, including in the analysis of microscopic images, immunohistochemical markers. Histopathology remains a fundamental pillar in tumour diagnosis, allowing pathologists to classify tissue sections, assess tumour grade and aggressiveness, and guide treatment using biomarkers such as ER and PR [13]. AI tools now enable precise quantification of proliferation markers like Ki-67, with excellent agreement to manual scoring (ICC 0.970–0.990), and can detect differences between lymphoma subtypes, for example, 80% in high-grade B-cell lymphoma versus 55% in diffuse large B-cell lymphoma [14]. Beyond quantification, AI assists in tasks such as cell segmentation, assessment of spatial cell arrangements, detection of isolated tumor cells in lymph nodes, and standardization of scoring systems like Gleason or breast cancer grading. Content-based image retrieval further allows pathologists to quickly find similar cases from large databases, supporting faster and more accurate diagnosis of rare or complex tumors. Together, these applications highlight how AI enhances reproducibility, efficiency, and diagnostic precision in modern pathology practice [15]. In this way, AI transforms pathology from a manual practice into a more precise and efficient discipline, supporting faster and more reliable clinical decisions.

### 3.3 AI in Emergency Medicine

Emergency medicine is an area of medicine where time and diagnostic accuracy are crucial. AI brings significant improvements, particularly in the context of triage.

Traditional triage often relies on clinicians' rapid assessments, which can be subjective and inconsistent, particularly under pressure. AI-driven triage systems address these limitations by processing large amounts of patient data—including vital signs, symptoms, medical history, and demographics—to categorize patients more objectively and quickly. These systems can evaluate multiple variables simultaneously, identify high-risk patients based on historical and real-time data, and dynamically adjust prioritization according to resource availability, helping optimize ED workflow and patient outcomes [16].

AI also enhances earlier stages of emergency care, especially emergency medical dispatch (EMD). AI also improves earlier stages of emergency care, particularly emergency medical dispatch (EMD). Studies show that 4.9%–11.3% of prehospital deaths are potentially preventable, and 25.8%–42.7% are definitely preventable, often due to delayed treatment, management errors, or limitations of rule-based dispatch algorithms. Dispatchers must quickly gather and document critical information, which can be challenging in complex or unpredictable situations. AI-based systems, such as Corti, analyze callers' speech in real time, suggest relevant follow-up questions, and help identify life-threatening conditions such as cardiac arrest. These systems combine automatic speech recognition with predictive models to support faster decision-making and more efficient dispatch of emergency services [17]. The integration of AI into both emergency medical dispatch and triage represents a breakthrough in emergency care. It transforms AI from a supportive tool into a key partner that assists dispatchers and emergency teams in making rapid, precise, and life-saving decisions across the entire chain of emergency response.

### 3.4 AI in Aesthetic Medicine

AI is also rapidly revolutionizing aesthetic medicine. Advanced algorithms enable the analysis of facial symmetry, assessment of the aging process, and prediction of treatment outcomes. This allows patients to preview realistic simulations before the procedure, contributing to more precise treatment planning aligned with their expectations. Robotic systems are increasingly used in procedures requiring high precision, such as hair transplantation and laser-based treatments, enhancing both accuracy and patient safety [18].

In addition, the implementation of AI in aesthetic medicine supports the standardization of patient assessment and consultation, helping to minimize subjective bias and reduce the risk of overcorrection. There is a growing need for validated, objective facial evaluation systems based on measurable indices such as the Facial Aesthetic Index (FAI), the Facial Youth Index (FYI), and the Skin Quality Index (SQI) to ensure comprehensive and reproducible aesthetic analysis. AI assessment protocols should also incorporate relevant patient variables such as age, gender, and ancestral background, account for sex-specific differences in skin characteristics, and exclude patients wearing make-up at baseline examination to maintain diagnostic accuracy [19]. Beyond clinical assessment, AI-driven 3D facial modeling further strengthens objective analysis in aesthetic and surgical planning. Recently developed open-source morphing software has enabled the generation of large synthetic 3D facial datasets, including up to 980 three-dimensional models derived from 20 baseline synthetic faces, each annotated with 28 standardized facial landmarks. Such datasets allow precise measurement of key nasal and facial parameters—such as alar base width, nasal bridge length, nasal tip

projection, face width, and face height—facilitating reproducible morphometric analysis. The availability of bulk-generated, landmark-labeled 3D models. It enhances the training of machine learning algorithms for automated landmark detection and outcome prediction. Moreover, it eliminates ethical and regulatory barriers associated with real patient scans. These advances further support the integration of AI into aesthetic medicine by promoting scalable, data-driven, and consistent facial evaluation [20]. Collectively, these developments highlight the transformative potential of AI in aesthetic medicine, not only as a technological innovation but also as a tool for establishing a more objective, standardized, and patient-centered clinical practice. By integrating validated assessment indices with individualized patient data, AI improves treatment predictability and enables more consistent aesthetic outcomes.

### **3.5 AI in Public Health**

Public health focuses on assessing population health, identifying risks, and organizing healthcare systems. Traditional monitoring methods relied on manual data collection and analysis, which were time-consuming and error-prone. AI automates these processes, improving both speed and accuracy. It enables real-time health surveillance, early outbreak detection, disease trend forecasting, and population-level risk assessment, supporting more effective healthcare planning and resource allocation. As AI continues to advance, it has the potential to strengthen disease prevention, enhance decision-making, and improve overall population health [21].

In practice, AI tools such as infrared thermal imaging and face recognition help identify individuals with abnormal temperature and close contacts, while disease prediction models provide personalized health advice. The FDA-approved autonomous system IDx-DR is capable of analyzing retinal images without human intervention to identify diabetic retinopathy, with detection rates of 87.4% for cases above mild severity and 89.5% for less severe cases. AI is also being utilized in oncology for detecting cancer and in real-time processing of colonoscopy footage to locate polyps. Additionally, AI platforms such as BANDIT can forecast the action mechanisms of anticancer agents and suggest optimal drug combinations, aiding in the creation of effective treatments while lowering failure rates and speeding up the approval process [22]. Overall, advances in AI are expanding its role in public health, from monitoring and predicting disease to supporting personalized prevention and health management. Integrating AI into healthcare systems enhances intervention precision and effectiveness, paving the way for a more proactive and holistic approach to population health.

## **4. Challenges of AI in Modern Medicine**

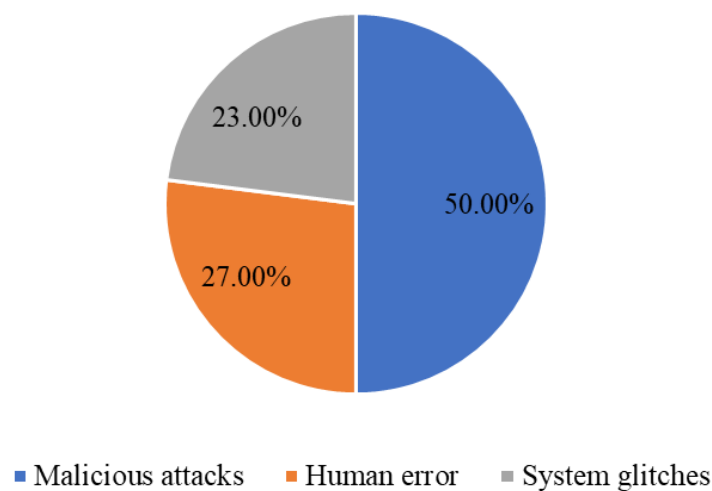
AI in medicine holds enormous potential. However, its implementation is associated with numerous challenges. These challenges are predominantly technical, clinical, organizational, and regulatory in nature and have a substantial impact on the reliability, safety, and scalability of AI-based solutions across healthcare systems. Their significance varies across different medical specialties, where differences in data types, clinical workflows, and risk levels influence practical application. Future development of AI in medicine involves the continued expansion of its clinical and research applications, strengthening its reliability and adaptability, and deeper integration into healthcare systems to support more effective and personalized care.

### **4.1. Data-related and Technical Challenges**

One of the major barriers to the clinical implementation of AI in medicine is the quality and representativeness of training data. AI models require large, high-quality datasets to achieve reliable and generalizable performance; however, medical data are often affected by noise, artefacts, and inconsistent annotation, which can compromise model robustness. Variations in patient populations, clinical settings, and healthcare practices across regions may further reduce generalizability and lead to inconsistent performance outside the original development context. Algorithmic bias can also result in uneven performance across subgroups, including differences in age, sex, or ethnicity. Moreover, the quality of the ground truth, such as imaging standards or molecular biomarkers used as surrogate endpoints imposes inherent limitations on model performance, as algorithmic predictions cannot exceed the reliability of the reference standards on which they are trained [1]. AI development is inherently data-intensive and requires not only imaging data but also metadata and clinical variables. Many studies rely on retrospective datasets to leverage large institutional databases, whereas prospective validation is necessary to confirm real-world applicability. Ensuring robust data governance, including secure storage, controlled access, quality control procedures, and compliance with privacy regulations is essential both for protecting patient confidentiality and for maintaining high data quality. In addition, cybersecurity vulnerabilities in healthcare systems increase the risk of data breaches and

ransomware attacks, which may compromise sensitive medical information and disrupt clinical services [23]. A review of 92 million procurement records from 36 countries showed that many devices used by national health services had serious vulnerabilities, often remaining unaddressed for an average of 3.2 years. This extended period of exposure can compromise sensitive medical data and disrupt clinical operations, emphasizing the importance of prioritizing device security alongside safety [24]. Human error has also been identified as a frequent cause of data compromise, highlighting the need for institutional safeguards and user training [23]. Since 2005, more than 380 million people in the U.S. have been affected by breaches of healthcare data, with roughly one-quarter of these incidents resulting from human mistakes. As Figure 1 illustrates, malicious attacks account for half of all breaches and system failures for nearly a quarter, a significant challenge remains the limited awareness among healthcare staff, as well as inadvertent or intentional actions by employees who regularly access electronic health records and other organizational information [25].

Causes of Data Breaches in Healthcare Sector



*Fig. 1. Proportion of causes of data breaches in the healthcare sector (data based on Alvarado and Triantis [25]).*

The integration of diverse data modalities introduces additional technical complexity. Multimodal AI systems that combine medical imaging, genomic sequencing data, and clinical variables require harmonization of heterogeneous data formats, alignment across different scales and measurement types, and effective handling of missing or inconsistent values. Ensuring seamless integration of these datasets is necessary for reliable model training and accurate predictions [26]. Algorithm robustness, interpretability, and reproducibility remain key technical concerns. AI models used in medical imaging may be vulnerable to distortions or adversarial manipulations, potentially leading to erroneous predictions, while their “black-box” nature limits transparency and clinicians’ trust. Although explainable AI techniques aim to improve interpretability, they do not always provide clinically meaningful insights. Furthermore, many models are developed using single-center datasets and optimized for specific conditions, increasing the risk of overfitting and limiting external validity. Inadequate reporting of data sources and improper data splitting may further result in overestimated performance and reduced generalizability [23]. Beyond initial development, maintaining long-term performance is equally critical. Temporal changes in clinical practice, patient demographics, and diagnostic technologies may shift data distributions over time, resulting in AI drift and progressive degradation of model accuracy. Additionally, AI hallucinations where systems generate plausible but factually incorrect outputs highlight fundamental limitations in reliability and underscore the importance of continuous post-deployment monitoring and validation in healthcare settings [27].

## 4.2. Regulatory and Standardization Challenges

The use of AI in healthcare is subject to a constantly changing regulatory environment, which can create uncertainty for developers and healthcare organizations. Variations in approval processes, certification standards, and post-deployment oversight between countries can make adoption more difficult, especially in public health settings that rely on interoperable, large-scale information systems. The lack of universally accepted guidelines for data sharing, model evaluation, and reporting continues to limit safe and efficient implementation. Since AI performance can shift over time due to evolving clinical practices and data patterns, regulatory approaches that support ongoing validation and continuous monitoring are particularly important [21]. Ensuring AI is used safely and effectively in healthcare requires strong oversight from regulatory authorities. Clear standards for data quality, model performance, and clinical validation are essential, alongside continuous monitoring to identify and resolve issues that arise in real-world settings. Because healthcare operates globally, international cooperation can help align ethical and regulatory practices, support interoperability, and enable the exchange of best practices. Determining responsibility and liability is often complicated when AI influences clinical decisions, so guidelines that clarify the roles of developers, healthcare providers, and institutions are critical [26]. After implementation, monitoring becomes more complex as AI systems gain the ability to independently recommend clinical actions, reprioritize studies, or modify workflow processes. Clinicians must retain final decision-making authority, while organizations should establish clear boundaries for autonomous AI functions and ensure secure, seamless integration with Radiology Information Systems (RIS), Picture Archiving and Communication Systems (PACS), and Electronic Health Records (EHR) without disrupting workflow or compromising cybersecurity. Early deployments should emphasize safety, transparency, and clinician oversight to build confidence in AI recommendations [28]. Trust in AI systems also depends on both substantial and procedural factors. Substantial trust is built on reliable data, sound methodological approaches, and a stable technological infrastructure. Procedural trust involves oversight, standardization, and management of organizational or technical processes [29]. Trust in AI systems in radiology can be understood in two dimensions: technical trust, which relates to the reliability of data, model performance, and infrastructure, and procedural trust, which involves standardized processes, oversight, system compatibility, and auditability. Evaluating AI tools also requires attention to potential algorithmic errors, how well models generalize to new or unseen data, and the risks posed by underrepresented cases in the training datasets [30]. Adoption may be affected by both financial and resource constraints. Beyond purchasing software licenses, healthcare institutions need to allocate funds for IT infrastructure, personnel training, ongoing system oversight, and routine maintenance. Smaller clinics, in particular, could struggle to justify these investments if reimbursement mechanisms are unclear or if the operational benefits are not clearly demonstrated [28]. Ensuring that AI systems are safe, reliable, and trustworthy in clinical practice requires not only appropriate regulations but also effective oversight and the active involvement of healthcare professionals in their implementation and monitoring [31].

## 4.3. Challenges across Medical Specialties

While the challenges of AI in medicine are widely recognized, their specific impact and practical implications differ considerably depending on the medical specialty. Each field faces unique obstacles shaped by the nature of its data, clinical workflows, and patient care requirements, making the integration of AI tools more complex in some areas than in others

### 4.3.1. Challenges of AI in Radiology and Pathology

The implementation of AI in radiology and pathology faces multiple technical, organizational, and workflow-related challenges that must be addressed to ensure reliable and clinically meaningful outcomes.

In radiology, the successful implementation of AI depends largely on how well these tools can be incorporated into everyday clinical practice. Rather than functioning as standalone applications, AI solutions must operate within established digital ecosystems, including Radiology Information Systems (RIS) and Picture Archiving and Communication Systems (PACS). Variability between vendors, institutional protocols, and data structures makes this integration technically and organizationally complex. If AI applications are introduced without adequate adaptation to local workflows, they may hinder rather than enhance efficiency, particularly when deployed across multiple healthcare institutions [6]. Incorporating AI into routine radiology practices presents technical and financial challenges. Medical institutions must establish suitable computational infrastructure and prepare radiologists to effectively utilize AI solutions, involving considerable costs and time commitments [32]. AI can also support diagnostic prioritization by flagging cases that may require urgent attention. However, its effectiveness depends on proper integration into routine clinical

workflows. Systems that generate too many alerts may disrupt radiologists' work, while insufficient sensitivity may reduce clinical value. For this reason, AI-based prioritization tools must be carefully calibrated and validated to ensure they enhance decision-making rather than create additional workflow challenges [6].

Pathology faces several technical challenges. Whole slide images (WSIs) can reach tens of billions of pixels, making training and inference computationally intensive. Dividing slides into smaller patches helps, but processing still takes considerable time, which can slow clinical workflows. AI in pathology also relies on high-quality annotated data, which is labor-intensive to produce and requires expert pathologists. Variations in staining, imaging equipment, and institutional practices add inconsistencies that reduce model reliability, while demographic imbalances and differing expert annotations limit generalizability. Predicting cancer outcomes requires capturing features across multiple scales from cells to tissue to whole-slide architecture but many models either analyze a single scale or combine multiscale data without fully representing interactions, potentially missing important prognostic information [33]. AI systems can often produce reliable results, yet understanding the reasoning behind their decisions remains challenging. This lack of clarity may reduce clinicians' confidence in these tools and slow their adoption in clinical settings. Employing visualization methods, like highlighting the most influential regions in an image, can help make AI decisions more transparent and interpretable [34].

#### **4.3.2. Challenges of AI in Emergency Medicine**

In emergency medicine, rapid decision-making demands real-time support from AI systems, placing high requirements on their reliability. Mistakes or delays in algorithmic outputs can have immediate clinical consequences, making it essential for AI tools to function accurately and integrate smoothly into urgent workflows. A well-documented limitation of large language models (LLMs) is "hallucination," where the system produces information that appears confident but is inaccurate or fabricated. In emergency settings, such misleading outputs can be especially dangerous, as they may be accepted as authoritative, potentially endangering patient safety. AI models generally perform best with common clinical scenarios, whereas rare or atypical cases are more likely to be misclassified—an important concern in emergency care, where unusual presentations frequently occur [35]. A significant challenge also concerns the quality of input data. Medical documentation in the emergency department (ED) is often created under intense time pressure and may be completed retrospectively. Moreover, certain clinically relevant information (e.g., overall clinical impression, subtle behavioral cues, or contextual observations) is not fully captured in electronic health records. Missing data, inconsistencies, or annotation errors can introduce systematic distortions in model performance. Therefore, AI systems designed for emergency settings should be capable of handling incomplete information robustly and explicitly accounting for the presence of missing data within the prediction process [17]. The use of AI in emergency medicine entails distinct operational and methodological limitations. Ensuring reliable performance in time-critical and data-imperfect environments remains a key prerequisite for its safe and effective integration into clinical practice.

#### **4.3.3. Challenges of AI in Aesthetic Medicine**

AI offers significant potential in aesthetic medicine by enabling more accurate and consistent assessment of skin conditions and supporting treatment planning. However, several challenges still limit its full effectiveness. One major issue is the variability and subjectivity of input data. Traditional approaches, such as the Baumann Skin Type Indicator, rely on patient questionnaires to evaluate factors like hydration, sensitivity, pigmentation, and wrinkles. While these methods are structured and cost-efficient, they remain inherently subjective and often fail to detect subtle differences in skin health. Likewise, objective measurements from instruments such as the Mexameter, Sebumeter, Cutometer, and Tewameter typically focus on small, localized areas, rather than capturing a complete picture. Comprehensive evaluations by clinicians, although detailed, are often coarse and may overlook minor changes in skin condition [36]. Limitations in raw data affect the accuracy and reliability of AI predictions. Another key challenge is dataset representativeness, as the quality of AI predictions largely depends on the diversity of training data. Many AI algorithms are trained on datasets that do not sufficiently capture variations in age, skin type, or ethnic background. Minority groups and certain age ranges are often underrepresented, and physiological differences—such as a higher number of corneocyte layers in individuals with darker skin—can lead to biased outputs and less accurate recommendations. Ensuring that AI systems are trained on diverse and representative datasets is therefore essential for fair performance and reliable outcomes across all patient groups [18]. Another important issue is the potential for excessive reliance on AI outputs, which could undermine clinical judgment. Although AI can enhance diagnostic accuracy, aesthetic medicine is ultimately guided by individual goals and personalized care. Depending too heavily on algorithms may lead to rigid, formulaic approaches that fail to account for psychosocial and cultural

factors. For example, AI might emphasize idealized facial symmetry over a patient's personal aesthetic preferences. Therefore, clinicians should treat AI as a complementary tool, applying their professional expertise to interpret algorithmic suggestions in light of each patient's unique needs [36].

#### 4.3.4. Challenges of AI in Public Health

Despite its transformative potential, the implementation of AI in public health faces substantial technical and systemic challenges. A key difficulty concerns the selection and optimization of appropriate AI models for highly complex, multimodal datasets that integrate omics data, clinical records, and population-level determinants. The scale, heterogeneity, and multidimensionality of such data complicate algorithm design and increase the risk of limited robustness or reduced generalizability if models are not properly validated. Moreover, AI performance depends heavily on access to standardized, high-quality, and well-curated datasets. Fragmentation, inconsistent data collection practices, and limited harmonization across institutions remain significant barriers. Consequently, the development of coherent validation strategies and harmonized assessment standards is essential to ensure reproducibility and applicability across diverse population datasets [37]. Beyond methodological constraints, structural and organizational factors further limit effective deployment. Many public health institutions operate on outdated digital infrastructures that are not designed for large-scale analytics or seamless interoperability. Limited data-sharing strategies, insufficient policy frameworks for big data use, and uneven digital health governance slow AI integration. In parallel, workforce capacity remains constrained. Many public health professionals do not possess advanced AI-related competencies, and the rapid pace of technological development—combined with heavy operational demands—reduces the feasibility of sustained skills development. Additionally, the implementation of AI systems requires continuous human oversight throughout development, deployment, and routine use to ensure proper functioning and clearly defined accountability structures within health systems [21]. These challenges become particularly evident when translating AI innovations from research settings into large-scale public health systems. Addressing technical, infrastructural, and workforce-related barriers is therefore essential for the responsible and effective scaling of AI in public health practice.

Table 1 below summarizes the most important applications, implementations, and challenges of AI in medicine. The potential for AI use in healthcare is growing, although numerous limitations must first be resolved before data-driven technologies become a standard component of clinical practice.

**Table 1.** Summary of Examples, Implementation, and Challenges in the Application of AI in Medicine.

AI Application Area	Example Applications	Implementation and Effectiveness	Challenges and Limitations
Radiology	Image analysis, cancer and cardiovascular disease detection, endovascular interventions.	Widely used in research; increasing clinical adoption.	Integration with RIS/PACS, black box issues, bias, training requirements.
Pathology	Whole-slide image analysis, automated Ki-67 scoring, tumor classification.	Deployed in digital labs, limited to specialized centers.	Large images, annotation requirements, data variability, generalization.
Emergency Medicine	Triage, sepsis risk prediction, dispatcher call analysis.	Early implementations in hospitals and EMD.	LLM hallucination in rare/urgent cases, data scarcity, time-critical decisions.
Aesthetic Medicine	Procedure simulation, facial symmetry analysis, robotics in procedures.	Limited, growing adoption in private clinics.	Subjective data, bias against underrepresented groups, overreliance on AI.
Public Health	Disease monitoring, early epidemic detection, trend prediction.	Implemented in public health agencies, pilot systems.	Fragmented data, lack of interoperability, insufficient staff expertise.

## 5. Future Directions of AI in Modern Medicine

A critical future direction in the clinical implementation of AI involves not only the systematic post-deployment monitoring of models, but also their expanding role in biomedical research and scientific discovery [26]. By handling routine administrative tasks, AI can help healthcare providers work more efficiently, giving them greater opportunity to focus on patient interaction and reinvigorating the personal, face-to-face aspect of care [38]. Since clinical data are constantly changing due to shifts in patient populations, diagnostic procedures, and disease trends, AI systems need ongoing performance monitoring to identify data drift and implement updates as needed, ensuring sustained diagnostic accuracy, patient safety, and dependable long-term performance [26]. Drug discovery and development stand out as an exciting but demanding domain for AI. Approaches driven by AI streamline molecular design, forecast drug–target interactions, cut development expenses, accelerate timelines, and enhance the likelihood of successful outcomes [1]. Simultaneously, progress in machine learning is driving more effective analysis of large, complex, and multimodal datasets, speeding up the identification of biomarkers in areas like genomics, radiomics, and pathomics, and facilitating a more integrated approach to precision medicine across multiple omics layers [26]. In clinical settings, AI is poised to play an increasingly prominent role in supporting medical decision-making, especially in high-pressure areas like emergency care [39]. Combining AI with growing digital biobanks is set to enhance research scalability, refine patient stratification, and optimize clinical trial design, establishing AI as a self-improving clinical tool and a central force in translational research, reflecting the rise of new generalist foundation models that integrate diverse types of clinical data [26]. Initial applications in predicting sepsis, assessing infection risk, and prioritizing radiology cases indicate that AI-driven decision support is steadily advancing and becoming more embedded in real-time clinical workflows. Machine learning models are expected to increasingly aid clinicians in analyzing imaging studies, highlighting urgent findings, forecasting patient deterioration, and streamlining triage processes [39]. In addition to improving operational efficiency, AI and machine learning enable the integration and analysis of diverse and complex datasets, supporting the development of personalized treatment plans. By influencing every stage of care from risk assessment and diagnosis to therapy selection, monitoring, and outcome evaluation these technologies advance precision medicine while promoting a more proactive, data-driven, and patient-centered approach to healthcare [38].

## 6. Ethical Considerations of AI in Modern Medicine

The development of AI-based tools has significantly impacted the way diseases are diagnosed and treated, enabling faster analysis of medical data, improved diagnostic accuracy, and more precise tailoring of therapy to individual patient needs [2, 4, 40]. Applications of AI in fields such as radiology, pathology, and public health demonstrate its significant potential to improve the quality of healthcare, optimize clinical workflows, and improve the efficiency of healthcare system resources. It is crucial to recognize that AI is designed to assist and enhance the work of healthcare professionals, allowing them to concentrate on more complex and high-priority tasks rather than replacing their role. Delegating routine and repetitive tasks to automated systems can reduce the workload of healthcare staff, enabling them to focus more on patient care and valuable interpersonal interactions [40]. Medical ethics, grounded in beneficence, non-maleficence, autonomy, and justice, now extends to the design and application of AI systems to ensure they are safe, transparent, and equitable [4]. Key ethical considerations related to the implementation of AI in healthcare include data bias, lack of transparency, explainability, the black box phenomenon, data privacy, responsibility in decision - making.

### 6.1. Data Bias

One of the most significant ethical challenges in medical AI is data bias and its impact on fairness in clinical decision-making. AI systems depend on the data used for training, and if these data reflect existing societal or systemic biases, the resulting models are likely to reproduce or even amplify them. Bias in training data is largely unavoidable, as medical datasets are generated by humans and embedded within social, cultural, and institutional contexts. Consequently AI models may inherit these biases, leading to discriminatory or unjust outcomes in clinical practice [2]. When data disproportionately represent a single demographic group, diagnostic or predictive models may perform less accurately for underrepresented groups, resulting in disparities in treatment [40]. For example, dermatological AI systems trained predominantly on images of lighter skin tones demonstrate reduced accuracy when applied to patients with darker skin, increasing the risk of misdiagnosis [4]. To reduce bias, efforts should focus on compiling datasets that adequately reflect the diversity of patient populations, including those that are often underrepresented in medical data [2, 4].

## 6.2. Transparency, Explainability and Black Boxes

The lack of transparency in AI systems is a significant issue, as it directly affects human health and well-being [2]. This opacity can make it difficult to identify and correct errors, undermine the trust of healthcare professionals and patients, and complicate the implementation of AI in medical practice [40, 41]. Many AI systems operate as “black boxes,” with complex algorithms that are difficult for humans to interpret, making it hard to understand how they reach decisions [2]. Explainability in AI seeks to address this by making system outputs understandable, for example through techniques like SHAP or LIME, which show which features most influence a prediction [4]. Without such explanations, models can rely on irrelevant features or dataset artifacts rather than meaningful clinical information, which may lead to flawed or unsafe predictions. By revealing the reasoning behind model outputs, explainable AI allows practitioners to detect errors, evaluate limitations, and safely integrate AI into medical workflows [42]. Another approach is to use simpler, more transparent models, such as decision trees or rule-based systems, whenever possible. Visualization tools can also help by presenting data and AI outputs clearly, making it easier for clinicians to interpret results [4].

## 6.3. Data Privacy

AI systems that utilize large-scale health data encounter significant ethical and legal challenges concerning the protection of patient privacy and the security of sensitive information [4]. Ensuring the security and confidentiality of the data utilized by AI is essential at multiple levels, including protecting the proprietary interests of companies holding AI patents and, perhaps most critically, guarding against unauthorized access by external parties, such as competing organizations or hackers [2]. The widespread use of electronic health records, telemedicine, and AI has greatly increased the collection and sharing of sensitive patient information, raising risks related to unauthorized access and data misuse. AI systems amplify these concerns, as they rely on large datasets that may contain personal health data, making transparency and informed consent essential to ensure ethical use [43]. AI applications face significant privacy challenges, particularly the risk that sensitive health information could be exposed through unauthorized access, potentially resulting in harm or discrimination. Even datasets that have been anonymized may be at risk of re-identification when combined with other sources of information. Moreover, utilizing patient data for AI purposes beyond the original clinical context raises critical consent concerns. In the United States, the Health Insurance Portability and Accountability Act (HIPAA) provides a legal framework for the protection and confidentiality of patient health information [4]. Similarly, the European Union’s General Data Protection Regulation (GDPR) enforces strict rules on data handling, highlighting the importance of obtaining patient consent, limiting data collection to what is necessary, and upholding the right to have personal data erased [2, 4]. To mitigate these risks, it is important to adopt strategies such as limiting data collection to what is strictly necessary, thereby minimizing unnecessary exposure. Maintaining data security through encryption and controlled access further protects information integrity. Federated learning provides an additional safeguard by allowing models to be trained on local datasets while sharing only aggregate updates, rather than raw patient data [4]. Emerging technologies like blockchain offer potential solutions for secure storage and sharing of health records, but regulatory frameworks must evolve to keep pace with technological advances and protect patient privacy [43]. Ensuring that patients are fully informed about the collection, storage, and use of their data remains a fundamental component of ethical AI deployment [4].

## 6.4. Responsibility in Decision - Making

Assigning responsibility for clinical decisions guided by AI presents significant ethical challenges, as these systems do not possess agency like human clinicians, yet their recommendations can have a direct impact on patient care [4]; although healthcare professionals are responsible for validating AI-generated decisions, they often have a limited role in the decision-making process and may not fully understand how the AI arrived at its conclusions [2]. Determining accountability when an AI system causes patient harm raises complex questions involving developers, healthcare professionals, and healthcare institutions [4]. Attributing responsibility in the context of AI-supported decisions may depend on the final clinical outcome. The same decision-making process can be judged differently depending on whether the patient outcome is positive or negative, as evaluations often focus more on the result than on the reasoning and circumstances present at the time the decision was made [44]. Challenges increase when AI suggestions diverge from clinician decisions, and current legal regulations offer little clarity on liability for AI-related medical errors. Recent approaches advocate for shared responsibility frameworks that clearly define the roles of AI developers, healthcare professionals, and institutions while establishing transparent accountability mechanisms. Maintaining

comprehensive audit records of AI outputs and corresponding clinical actions facilitates investigations, and ethical governance also requires oversight bodies to continuously assess system performance, monitor potential risks, and ensure compliance with standards [4].

## 7. Conclusions

The integration of AI into modern medicine represents a paradigm shift in how healthcare is delivered and experienced. Beyond its role in improving diagnostic accuracy and operational efficiency, AI has the potential to reshape the relationships between clinicians and patients by allowing medical professionals to focus more on individualized care and complex decision-making, rather than routine or repetitive tasks. Each medical specialty faces unique challenges in adopting AI from the computational demands of whole-slide pathology images to the high-stakes, time-critical nature of emergency medicine, and the subjective, patient-centered requirements of aesthetic practice. Ethical considerations remain central, requiring careful attention to fairness, transparency, accountability, and the protection of sensitive health data. Looking forward, sustainable implementation will rely on robust clinical validation, continuous performance monitoring, interdisciplinary collaboration, and the development of equitable and representative datasets. With these safeguards, AI can become not merely a technological tool but a strategic partner in advancing precision medicine, improving population health, and fostering a healthcare ecosystem that is more proactive, patient-centered, and resilient to future challenges.

## REFERENCES

1. Carini, C., & Seyhan, A. A. (2024). Tribulations and future opportunities for artificial intelligence in precision medicine. *Journal of Translational Medicine*, 22, 411. <https://doi.org/10.1186/s12967-024-05067-0>
2. Marques, M., Almeida, A., & Pereira, H. (2024). The medicine revolution through artificial intelligence: Ethical challenges of machine learning algorithms in decision-making. *Cureus*, 16(9). <https://doi.org/10.7759/cureus.69405>
3. Basubrin, O. (2025). Current status and future of artificial intelligence in medicine. *Cureus*, 17(1). <https://doi.org/10.7759/cureus.77561>
4. Gowda, U. (2025). Ethical AI in medicine: Balancing innovation with regulation and compliance. *International Journal of Science and Technology*, 2(1), 34. <https://www.ijstjournal.com/papers/volume-2/issue-1/ijst241024/>
5. Chustecki, M. (2024). Benefits and risks of AI in health care: Narrative review. *Interactive Journal of Medical Research*, 13. <https://doi.org/10.2196/53616>
6. Bhandari, A. (2024). Revolutionizing radiology with artificial intelligence. *Cureus*, 16(10). <https://doi.org/10.7759/cureus.72646>
7. Lesaunier, A., Khlaut, J., Dancette, C., Tselikas, L., Bonnet, B., & Boeken, T. (2025). Artificial intelligence in interventional radiology: Current concepts and future trends. *Diagnostic and Interventional Imaging*. <https://doi.org/10.1016/j.diii.2024.08.004>
8. Carriero, S., Cannella, R., Cicchetti, F., Angileri, A., Bruno, A., Biondetti, P., Colciago, R. R., D'Antonio, A., Della Pepa, G., Grassi, F., Granata, V., Lanza, C., Santicchia, S., Miceli, A., Piras, A., Salvestrini, V., Santo, G., Pesapane, F., Barile, A., Carrafiello, G., & Giovagnoni, A. (2025). AI revolution in radiology, radiation oncology and nuclear medicine: Transforming and innovating the radiological sciences. *Journal of Medical Imaging and Radiation Oncology*, 69(6), 649–659. <https://doi.org/10.1111/1754-9485.13880>
9. Lin, C., Tsai, D. J., Wang, C. C., Chao, Y. P., Huang, J. W., Lin, C. S., & Fang, W. H. (2024). Osteoporotic precise screening using chest radiography and artificial neural network: The OPSCAN randomized controlled trial. *Radiology*, 311(3). <https://doi.org/10.1148/radiol.231937>
10. Glielmo, P., Fusco, S., Gitto, S., Zantonelli, G., Albano, D., Messina, C., Sconfienza, L. M., & Mauri, G. (2024). Artificial intelligence in interventional radiology: State of the art. *European Radiology Experimental*, 8, 62. <https://doi.org/10.1186/s41747-024-00452-2>
11. Langlotz, C. P. (2023). The future of AI and informatics in radiology: 10 predictions. *Radiology*, 309(1). <https://doi.org/10.1148/radiol.231114>
12. Guo, L., Zhou, C., Xu, J., et al. (2024). Deep learning for chest X-ray diagnosis: Competition between radiologists with or without artificial intelligence assistance. *Journal of Digital Imaging*, 37, 922–934. <https://doi.org/10.1007/s10278-024-00990-6>
13. Ivanov, V., Khalid, U., Gurung, J., Dimov, R., Chonov, V., Uchikov, P., Kostov, G., & Ivanov, S. (2025). Use of AI histopathology in breast cancer diagnosis. *Medicina*, 61(10). <https://doi.org/10.3390/medicina61101878>
14. Cristian, M., Aşchie, M., Deacu, M., Boşoteanu, M., Bălţătescu, G. I., Stoica, A. G., Nicolau, A. A., Poinăreanu, I., & Orăşanu, C. I. (2023). Comparison of Ki67 proliferation index in gastrointestinal non-Hodgkin large B-cell lymphomas: The conventional method of evaluation or AI evaluation? *Diagnostics*, 13(17), 2775. <https://doi.org/10.3390/diagnostics13172775>

15. Shafi, S., & Parwani, A. V. (2023). Artificial intelligence in diagnostic pathology. *Diagnostic Pathology*, 18, 109. <https://doi.org/10.1186/s13000-023-01375-z>
16. Da'Costa, A., Teke, J., Origbo, J. E., Osonuga, A., Egbon, E., Olawade, D. B., et al. (2025). AI-driven triage in emergency departments: A review of benefits, challenges, and future directions. *International Journal of Medical Informatics*, 197. <https://doi.org/10.1016/j.ijmedinf.2025.105838>
17. Chenais, G., Lagarde, E., & Gil-Jardiné, C. (2023). Artificial intelligence in emergency medicine: Viewpoint of current applications and foreseeable opportunities and challenges. *Journal of Medical Internet Research*, 25. <https://doi.org/10.2196/40031>
18. Al-Dhubaibi, M. S., Mohammed, G. F., Atef, L. M., Bahaj, S. S., Al-Dhubaibi, A. M., & Bukhari, A. M. (2025). Artificial intelligence in aesthetic medicine: Applications, challenges, and future directions. *Journal of Cosmetic Dermatology*, 24(6). <https://doi.org/10.1111/jocd.70241>
19. Frank, K., Day, D., Few, J., Chiranjiv, C., Gold, M., Sattler, S., et al. (2024). AI assistance in aesthetic medicine: A consensus on objective medical standards. *Journal of Cosmetic Dermatology*, 23(12), 4110–4115. <https://doi.org/10.1111/jocd.16481>
20. Topsakal, O., Gllinton, J., Celikoyar, M. M., et al. (2023). Open-source 3D morphing software for facial plastic surgery and facial landmark detection research and open access face data set based on deep learning (artificial intelligence) generated synthetic 3D models. *Facial Plastic Surgery & Aesthetic Medicine*, 26(2). <https://doi.org/10.1089/fpsam.2023.0030>
21. Panteli, D., Adib, K., Buttigieg, S., Goiana-da-Silva, F., Ladewig, K., Azzopardi-Muscat, N., Figueras, J., Novillo-Ortiz, D., & McKee, M. (2025). Artificial intelligence in public health: Promises, challenges, and an agenda for policy makers and public health institutions. *Lancet Public Health*, 10(5). [https://doi.org/10.1016/S2468-2667\(25\)00036-2](https://doi.org/10.1016/S2468-2667(25)00036-2)
22. Wang, X., He, X., Wei, J., Liu, J., Li, Y., & Liu, X. (2023). Application of artificial intelligence to the public health education. *Frontiers in Public Health*, 10. <https://doi.org/10.3389/fpubh.2022.1087174>
23. Saw, S. N., & Ng, K. H. (2022). Current challenges of implementing artificial intelligence in medical imaging. *Physics in Medicine*, 100, 12–17. <https://doi.org/10.1016/j.ejmp.2022.06.003>
24. Bracciale, L., Loreti, P., & Bianchi, G. (2023). Cybersecurity vulnerability analysis of medical devices purchased by national health services. *Scientific Reports*, 13. <https://doi.org/10.1038/s41598-023-45927-1>
25. Alvarado, W., & Triantis, K. (2024). Human error in data breaches of electronic health records (EHR): Systematic literature review. *Journal of Industrial Engineering and Management Studies*, 11(1), 19–40. <https://doi.org/10.22116/jiems.2024.418211.1533>
26. Hanna, M. G., Pantanowitz, L., Dash, R., Deebajah, M., Pantanowitz, J., & Rashidi, H. H. (2025). Future of artificial intelligence—Machine learning trends in pathology and medicine. *Modern Pathology*. Advance online publication. <https://doi.org/10.1016/j.modpat.2025.100705>
27. Namazi, H., & Radfar, M. M. (2025). Philosophy of medicine meets AI hallucination and AI drift: Moving toward a more gentle medicine. *Journal of Medical Ethics and History of Medicine*, 18(2). <https://doi.org/10.18502/jmehm.v18i2.18812>
28. Dietrich, N. (2025). Agentic AI in radiology: Emerging potential and unresolved challenges. *British Journal of Radiology*, 98(1174), 1582–1584. <https://doi.org/10.1093/bjr/tqaf173>
29. Bergquist, M., Rolandsson, B., Gryska, E., Laesser, M., Hoefling, N., Heckemann, R., et al. (2023). Trust and stakeholder perspectives on the implementation of AI tools in clinical radiology. *European Radiology*, 34(1), 338–347. <https://doi.org/10.1007/s00330-023-09967-5>
30. Rossa, J., Hammouche, S., Chen, Y., Rockall, A. G., & Royal College of Radiologists AI Working Group. (2024). Beyond regulatory compliance: Evaluating radiology artificial intelligence applications in deployment. *Clinical Radiology*, 79(5), 338–345. <https://doi.org/10.1016/j.crad.2024.01.026>
31. Cheng, J. Y., Abel, J. T., Balis, U. G. J., McClintock, D. S., & Pantanowitz, L. (2021). Challenges in the development, deployment, and regulation of artificial intelligence in anatomic pathology. *American Journal of Pathology*, 191(10), 1684–1692. <https://doi.org/10.1016/j.ajpath.2020.10.018>
32. Zalewa, K., Olszak, J., Kaplan, W., Orłowska, D., Bartoszek, L., Kaus, M., & Klepacz, N. (2025). Application of artificial intelligence in radiological image analysis for pulmonary disease diagnosis: A review of current methods and challenges. *Journal of Education, Health and Sport*, 77. <https://doi.org/10.12775/JEHS.2025.77.56893>
33. Zhang, X. M., Gao, T. H., Cai, Q. Y., Xia, J. B., Sun, Y. N., Yang, J., et al. (2026). Artificial intelligence in digital pathology diagnosis and analysis: Technologies, challenges, and future prospects. *Military Medical Research*, 12. <https://doi.org/10.1186/s40779-025-00680-6>
34. Debnath, J. (2023). Radiology in the era of artificial intelligence (AI): Opportunities and challenges. *Medical Journal Armed Forces India*, 79(4), 369–372. <https://doi.org/10.1016/j.mjafi.2023.05.003>
35. Amiot, F., & Potier, B. (2025). Artificial intelligence (AI) and emergency medicine: Balancing opportunities and challenges. *JMIR Medical Informatics*, 13. <https://doi.org/10.2196/70903>
36. Thunga, S., Khan, M., Cho, S. I., Na, J. I., & Yoo, J. (2024). AI in aesthetic/cosmetic dermatology: Current and future. *Journal of Cosmetic Dermatology*, 24(1). <https://doi.org/10.1111/jocd.16640>

37. Venturini, P., Lobato Faria, P., & Cordeiro, J. V. (2025). AI and omics technologies in biobanking: Applications and challenges for public health. *Public Health*, 243. <https://doi.org/10.1016/j.puhe.2025.105726>
38. Rojas-Carabali, W., Cifuentes-González, C., Gutierrez-Sinisterra, L., Heng, L. Y., Tsui, E., Gangaputra, S., et al. (2024). Managing a patient with uveitis in the era of artificial intelligence: Current approaches, emerging trends, and future perspectives. *Asia-Pacific Journal of Ophthalmology*, 13(4). <https://doi.org/10.1016/j.apjo.2024.100082>
39. Petrella, R. J. (2024). The AI future of emergency medicine. *Annals of Emergency Medicine*, 84, 139–153. <https://doi.org/10.1016/j.annemergmed.2024.01.031>
40. Kennet, P., & Falkner, S. (2025). The ethical frontier: AI in medicine and dentistry. *Journal of Medical and Clinical Case Reports*, 2(2). <https://doi.org/10.61615/JMCCR/2025/MAY027140516>
41. Bekbolatova, M., Mayer, J., Ong, C. W., & Toma, M. (2024). Transformative potential of AI in healthcare: Definitions, applications, and navigating the ethical landscape and public perspectives. *Healthcare*, 12(2). <https://doi.org/10.3390/healthcare12020125>
42. Marcus, E., & Teuwen, J. (2024). Artificial intelligence and explanation: How, why, and when to explain black boxes. *European Journal of Radiology*, 173. <https://doi.org/10.1016/j.ejrad.2024.111393>
43. Shoghli, A., Darvish, M., & Sadeghian, Y. (2024). Balancing innovation and privacy: Ethical challenges in AI-driven healthcare. *Journal of Review of Medical Sciences*, 4(1). <https://doi.org/10.22034/jrms.2024.494112.1034>
44. Edwards, C., Murphy, A., Singh, A., Daniel, S., & Chamunyonga, C. (2025). The role of patient outcomes in shaping moral responsibility in AI-supported decision making. *Radiography*, 31(3). <https://doi.org/10.1016/j.radi.2025.102948>