Ethical and Clinical Implications of Artificial Intelligence in Diagnostic Medicine

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Artificial intelligence (AI) is becoming a major transformative force in diagnostic medicine because it allows predicting the disease more accurately and raises the level of clinical efficiency. State-of-the-art machine learning models trained on large-scale integrated datasets have made it possible to have AI systems analyze medical imaging, histopathology samples, and electronic health records at a level comparable to human experts. Irrespective of these developments, there are serious ethical, clinical, and governance issues concerning the extensive use of AI in diagnosis. In this paper, a systematic narrative review of these concerns will be presented based on 30 peer-reviewed publications found in PubMed, IEEE Xplore, Scopus, and Google Scholar, and relating to the years 2023-2025. With the help of Boolean search strategies, the review identifies algorithmic bias, explainability, and data privacy as key ethical issues, each reported in more than 60% of the reviewed studies. The most critical regulatory weaknesses were found to be governance gaps and a lack of monitoring of post-deployment. The results underscore a long-standing trade-off between model performance and explainability, and the necessity of human-in-the-loop systems to maintain clinical judgment and patient trust. Implementing AI responsibly involves strong governance mechanisms and Tran's disciplinary teams of technologists, clinicians, ethicists, and policymakers to create fair and patient-focused AI diagnostics.

Keywords: Explainable Artificial Intelligence, Ethical Frameworks, Diagnostic Medicine, Privacy-Preserving Methods

Introduction:

Diagnostic medicine is one of the fields where AI is demonstrating real clinical value [1]. Diagnostic medicine is a key field where AI is demonstrating clinical value. The implementation of AI in clinical practice leads to a certain pattern of ethical, legal, and social concerns that should be addressed in an interdisciplinary manner. This paper critically discusses the recent findings on the use of artificial intelligence in diagnostic medicine and its ethical considerations, governance approach, and clinical significance in particular. This study establishes the most severe ethical risks, evaluate the existing regulatory practices, and identify research gaps to support responsible AI adoption of AI in healthcare. The present paper elaborates on potential ethical, clinical, and governance implications of artificial intelligence in diagnostic medicine in a systematic review of the available literature on the topic. The article identifies common ethical dilemmas, evaluates current regulatory trends, and fills the gaps compromising the responsible application of AI in healthcare systems through the analysis of interdisciplinary studies in the medical, technical, and policy spheres. Medical imaging, pathology, and electronic health records are analyzed using artificial intelligence to enable routine screening and complicated diagnoses. Advances in deep learning, big data analytics, and large clinical datasets have been the motivation behind the use of AI in the triage process, risk prediction, and optimization of workflows. Nevertheless, there are still problems of interpretation, fairness, and privacy of data [2]. Its applications include automated analysis of imaging, optimization of pathology workflow, and predictive modeling. The convolutional neural networks (CNNs) and similar structures have reached or even surpassed human capability in cancer-finding, lung pathology, and retinal pathology. AI is therefore beginning to be a part of the next-generation practice of diagnostic radiology, pathology, and genomics.

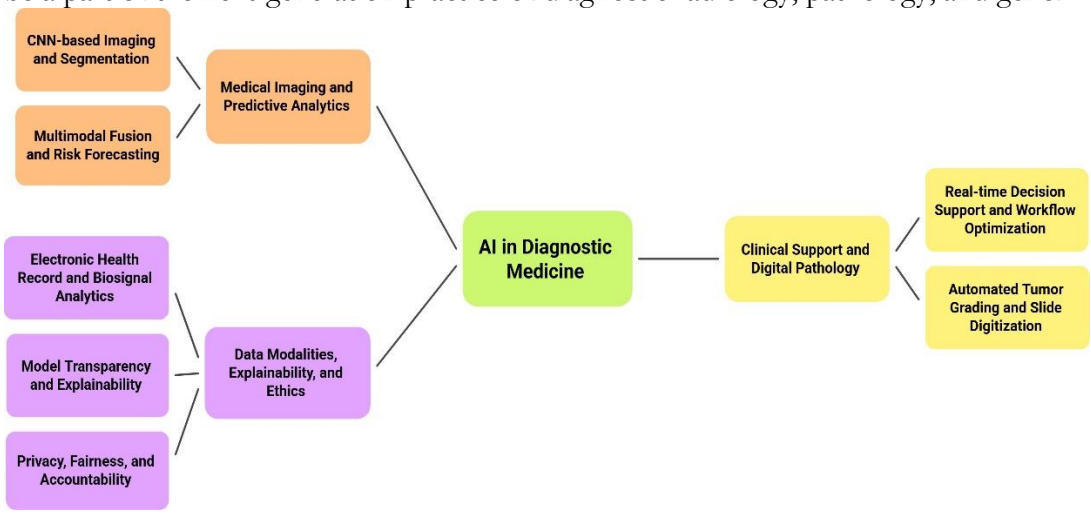


Figure 1. AI in Diagnostic Medicine: Key Domains

Figure 1 shows the major fields of AI implementation in diagnostic medicine, including medical imaging, biosignal analysis, EHR integration, and data ethics. The thematic organization of the review was facilitated by this taxonomy. The full benefits of AI can only be achieved through well-developed ethical standards and strong regulatory policies. [3][4]. Current implementations are based on unsupervised learning, supervised paradigm, and reinforcement learning. Despite these developments, there are still issues with the interpretability, scalability, and regulatory concerns. Some of the areas promising development include multi-modal data fusion, integrating imaging modalities, bio signals, and electronic health records, as well as explainable artificial intelligence methods that enhance prediction accuracy and the confidence of clinicians. The validation of cross-setting in the future, longitudinal assessment, and achieving fair results in artificial intelligence-enabled diagnostics are the main priorities of future research [5].

Diagnostic artificial-intelligence has developed out of the rule-based computational models of the 1980s to modern deep-learning models, including transformers and ResNet. This is through the use of transfer learning and large datasets such as ImageNet to achieve realism and generalize to a wide variety of tasks. A number of AI-based diagnostic tools have already received FDA approval, thus validating their conversion into the validated clinical systems [6]. The following are the key contributions of this paper.

Gives a systematic review of ethical issues like prejudice, privacy, transparency, and responsibility in AI-based diagnostic systems.

Consider recent multi-disciplinary literature (2023-2025) of medical, engineering, and Policy research communities.

Determines regulatory and governance loopholes in the practical use of AI diagnostics.

Brings out the importance of explainable AI and human-in-the-loop models in sustaining clinical trust.

Describes gaps in research and future opportunities for responsible and patient-centered adoption of AI in healthcare.

Although the current reviews focus on either technical performance or ethical principles separately, not many studies combine both the ethical and clinical aspects of governance in a single framework.

Methodology:

In this paper, a systematic narrative review is performed. The relevant literature was located with the help of a specific search in various academic databases that address the fields of technical, clinical, and interdisciplinary research. Four main databases that were used are as follows.

PubMed - specialized in clinical and medical research articles.

IEEE Xplore - archiving technical and AI engineering publications.

Scopus and Web of Science offer a wider range of peer-reviewed research.

Google Scholar - provides other scholarly articles, reports, and policy publications. Publications published in the last three years (2023-25) in English were considered, but restricted to peer-reviewed journal articles and conference papers dedicated to AI in diagnostic medicine and containing the full text. Abstract-only sources, non-English publications, treatment-only studies, and editorial and opinion pieces were excluded.

Keywords and Searching:

Search terms and combinations of keywords were developed to cover both technical and ethical aspects of the topic. The use of the Boolean operators was made to combine the terms and increase the relevance of the results. Examples of key search terms were:

Artificial intelligence, machine learning, deep learning, diagnostic medicine, clinical decision support, medical imaging, ethical challenges, algorithmic bias, data privacy, explainability, AI governance, accountability, regulatory frameworks

One of the Boolean search queries was: (artificial intelligence) OR (machine learning) OR (deep learning) AND (diagnostic medicine) OR (medical imaging) OR (clinical decision support) AND (ethics) OR (algorithmic bias) OR (explainability) OR (data privacy) OR (AI governance). The initial searches revealed about 340 articles, which were filtered by title and abstract to 89, and narrowed down to 30 final studies after the use of inclusion and exclusion criteria.

Synthesis and Thematic Analysis:

The literature chosen was qualitatively analyzed and structured based on the recurrent themes found during the review. The analysis was structured based on themes, which included privacy, bias and fairness, explainability, clinical integration problems, and accountability models. The themes identified were used to inform the conceptual discourse and illustrative frameworks that were presented subsequently. Even though the review does not follow the

elaborative replicable protocols that a formal systematic review is expected to follow, it has a clear and systematic method for literature identification and synthesis. This improves the clarity, potentiality, and credibility of the results, as the results are placed in a chosen scope of academic literature.

Fundamentals of AI in Diagnostic Medicine:

The field of AI in diagnostic medicine is based on statistical learning, neural network designs, and sophisticated data analytics to detect clinically relevant trends within multi-dimensional datasets. The recent developments have been facilitated by the availability of bigger volume data, novel neural architectures, and greater computational capability. Supervised and reinforcement learning algorithms routinely perform the automated extraction of features, predictive model construction, and biosignal interpretation, and popular methods are convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Multimodal combination also improves the quality of the diagnosis, whereas explainable AI (XAI) systems enable the transparency and confidence of clinicians [7]. The CNNs and RNNs are as well useful in interpreting medical pictures and time biosignals. XAI techniques describe the rule-of-thumb decision-making process, which leads to more clinical applications of it in clinical practice [8].

Artificial Intelligence and Machine Learning:

Transformer networks, convolutional neural networks, and recurrent neural networks are typically applied in image processing, sequential biosignal analysis, and sequential biosignal analysis, respectively. This is because of its heterogeneity of training datasets and rigorous validation processes, which are required to ensure the reliability of these systems [9]. AI assists in screening, triage, and prognosis by analyzing multiple modalities:

Medical Imaging: X-ray, CT, MRI, ultrasound.

Biosignals: ECG, EEG, and other physiological data.

Electronic Health Records (EHRs): Clinical history, labs, and prescriptions. Multimodal fusion provides a possibility to confirm the results gained through the use of different sources at the same time, wearable and remote sensing technologies increase the possibilities of predictive and preventive care, and contribute to the implementation of personalized medicine [10].

Applications in Diagnostics:

Artificial intelligence is the backbone of automated detection, predictive modeling, and decision support mechanisms, therefore, leading to increased diagnostic accuracy, operational efficiency, and enhanced provision of patient-centered care [11]. Artificial intelligence is used in pathology and radiology to complement the process of locating tumors, fractures, and abnormalities. Convolutional neural networks and ensemble models may often be more sensitive and specific than traditional ones, thus making it possible to intervene earlier and to implement a large-scale screening program [12]. Prognosticated disease development, danger of hospitalization, and therapeutic reaction are predictable through predictive models. DSSs combine multimodal data to create personalized evidence-based suggestions.

Ethical Challenges in AI-Enabled Diagnostics:

Artificial intelligence enhances the accuracy of diagnosis and efficiency of operations, but advanced algorithms raise serious ethical issues that include privacy, fairness, and transparency. The possible threat includes the misuse of the data, algorithmic bias, and the creation of damaging inferences.

Securing Privacy and Security:

One of the key principles is privacy. The General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) are some of the regulations that require data anonymization, access control, and informed consent [8]. The security of data depends on strong encryption, privacy-friendly protocols, and adherence to

the existing standards. Federated learning eliminates the necessity to exchange raw data, whereas Advanced Encryption Standard (AES) ensures the protection of information and prevents the participation of the re-identification risk by adding noise to the information [8].

$$Rprivacy = 1 - |Dleak||Dtotal| \quad (1)$$

Equation (1) measures privacy risk, where $|Dleak|$ is the compromised data and $|Dtotal|$ is the dataset size. This model is based on conventional methods of quantifying data privacy as presented in the literature on federated learning [13]. Ethical management will be informed, transparent, and with an audit trail. The mechanism of opt-in/ out would give the patient authority and accountability. Included in the academic regulations should be a good consent practice, a good data use notification, and a formal audit practice. Increasing the validity of the data governance may also be achieved by the use of blockchain-based consent verification and the application of digital watermarking.

$$S = Aconsent/A\ system \quad (2)$$

Here, S quantifies consent adherence, where Aconsent is the number of actions with valid consent, and a system is the total system actions.

Algorithmic Fairness and Transparency:

Bias comes in the shape of skewed distribution of data, drift in the model, or the absence of representation of vulnerable populations. Normalization of datasets, bias-sensitive learning, and frequent auditing are some of the possible mitigation measures. With the assistance of the most important metrics, i.e., the statistical part, the equalized odds, and the demographic part, the bias could be identified. The relevant mitigation strategies to such include data re-balancing, adversarial debiasing, and fairness-conscious modeling [14].

$$Fparity = P(\hat{Y} = 1|A = 0) - P(\hat{Y} = 1|A = 1) \quad (3)$$

Fparity measures prediction parity across groups. XAI promotes interpretability using methods such as SHAP, LIME, and feature heatmaps.

$$N\ Exai = \quad score\ (fi)/\ i{=}1 \quad (4)$$

Equation (4) quantifies explainability, where fi are feature contributions. This summation of the feature contribution scores is consistent with SHAP-based explainability techniques reported in the XAI healthcare literature [15][16].

Accountability, Consent, and Human Factors:

The three pillars of artificial intelligence-enhanced diagnostic systems are accountability, informed consent, and human-centered design. Several stakeholders, such as the European Union Medical Device Regulation (EU-MDR) and the directions of the United States Food and Drug Administration (US-FDA), share the responsibility for the liability of AI diagnostics [17]. Nevertheless, they also result in complicated legal problems regarding the liability in a diagnosis context in case of misdiagnosis [18]. Modern legal studies are becoming more interested in the problem of malpractice, product liability, and indemnity in the case of AI-enabled care.

$$L = \alpha D + \beta C + \gamma I \quad (5)$$

Equation (5) models total liability (L) as contributions from developers (D), clinicians (C), and institutions (I), weighted by α, β, and γ. This weighted liability scheme is in line with multi-stakeholder accountability models in AI medical law studies. Regulatory frameworks are going to be required to deal with AI, which will require the tightening of the process of approval, improvement of the post-market surveillance tool, and harsher performance criteria [19].

Informed Consent and Patient Autonomy:

Artificial intelligence that is put into practice in an ethically responsible environment involves close interaction with patients. To preserve patient autonomy and establish trust, clinicians are advised to clarify the purpose of the AI systems and explain the potential limitations of the latter.

A = Pc consent Pt (6)

The autonomy (Aconsent) is calculated as the ratio of the number of fully informed patients when it concerns the full population (Pt). Two variables in Equation (6). Risk visualization tools and interactive platforms facilitate informed consent by enhancing patient understanding and involvement [20]. AI should be an assistant to the clinical practice and not a replacement, and transparency and trust in the relationships between clinicians and patients should be ensured through open-ended consent and continuous communication between clinicians and patients [20]. Figure 2 describes the ethical paradigm of AI-enhanced diagnostics, which is based on five mutually supporting pillars, namely patient-centered data protection, data privacy and security, algorithmic fairness, human factors, and fair AI design, highlighting that ethical AI cannot be realized solely on a technical basis.

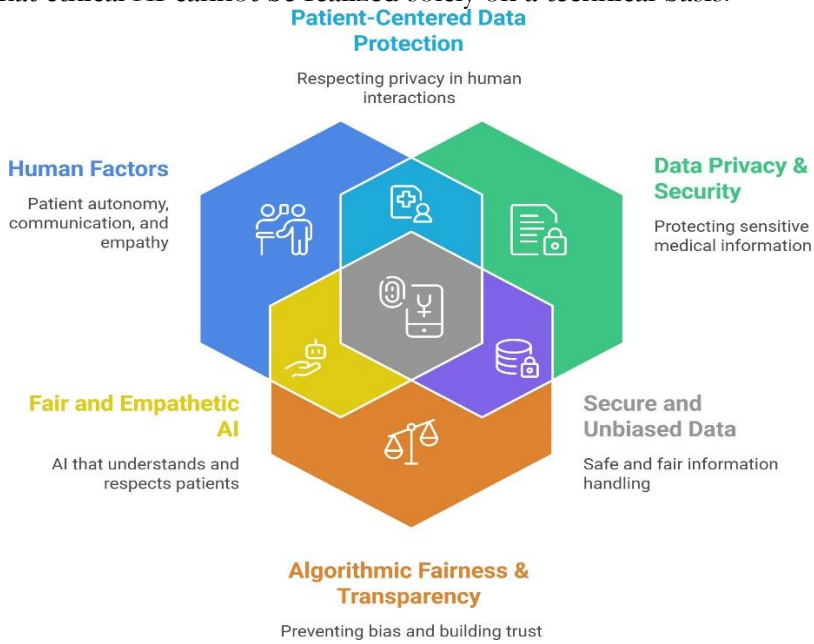


Figure 2. Ethical framework and stakeholder roles in AI-augmented diagnostic medicine

Clinical Implications and Performance:

AI can improve the quality of diagnostic procedures and the efficiency of the working process, particularly in the spheres of radiology and disease prevention. The attendant benefits include reduced diagnostic times, increased clinical outcomes, and efficient distribution of resources. However, a safe introduction of AI requires strict assessment, the systematic management of risks, and the development of a sense of confidence in clinicians [21][22][23].

Diagnostic Accuracy and Efficiency:

The modern AI systems have become par or even better than clinicians concerning many tasks. Deep generative architectures are highly sensitive and specific in radiographic interpretation, whereas large language models offer decision support. Also, AI supports a decrease in the time of review, especially in resource-limited settings. However, interpretability and wide clinical validation are also imperative conditions.

The accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) are used in evaluation and compared to expert annotations.

$$\int 1/0 \text{ AUC} = \text{TPR(FPR) dFPR} \quad (7)$$

Equation (7) defines the area under the curve, with TPR as the true positive rate and FPR as the false positive rate. The threats of artificial intelligence include excessive reliance, lack of vigilance, and generalization. The cumulative defect of diagnosis can be measured as:

$$E\text{total} = E\text{data} + E\text{model} + E\text{integration} \quad (8)$$

Mitigation requires oversight, monitoring, and iterative refinement.

Integration into Clinical Workflow:

Interoperability, extensive training, and the least operational disruption are the conditions of successful deployment. The systems should conform to the requirements of clinicians and provide explainability. Human-in-the-Loop Models suggest mixed methodologies combine the expertise of clinicians and AI-based findings:

$$S = wAISAI + wClinicianSClinician,\ wAI + wClinician = 1 \quad (9)$$

Equation (9) integrates AI (SAI) and clinician (SClinician) scores..

Other than accuracy, a robust evaluation structure requires the inclusion of the precision, the recall, and the F1-score:

$$F\ 1 = 2 \times \text{Precision} \times \text{Recall Precision} + \text{Recall} \quad (10)$$

These measures, in combination with the area under the receiver operating characteristic curve (AUC), contribute to the validation being robust.

Best Practices and Frameworks:

Ethical, efficient, and fair utilization of artificial intelligence is enabled by controlled systems. These models deal with technical, organizational, and patient-centric needs [24].

Developer Guidelines:

Fairness, accountability, and transparency have to be considered when developing artificial intelligence-based systems. Bias mitigation would be possible by integrating as many datasets as possible, continuous validation, and good documentation. The collaboration with the medical workers and the system strengthening, in turn, can only serve to enhance the capacity of the system to survive in further application. By implementing multiple approaches and tools, including the use of different data, systematic bias identification, and a well-documented life cycle, the researchers empower equity and transparency, which facilitates fairness and accountability in the data usage process. The ability to promptly address emerging biases is improved by regular audits, which also increase privacy, fairness, and accountability.

Clinical and Organizational Guidelines:

Institutional preparedness and training of clinicians are required. Interdisciplinary training improves AI literacy, unlike the patient-centered approaches that support autonomy and trust. Certain forms of training assist in the interpretation of the outcomes of AI securely and enhance the moral judgment of clinicians. The categories that ensure that AI does not pose a threat to clinical care and empathy are co-design and open communication.

Case Studies and Real-World Applications:

AI applications reduce diagnostic delay, enhance patient outcomes, and lower costs. However, the obstacles, such as the workflow integration, dataset bias, and lack of diversity, remain. It is also necessary to continue cooperating with clinicians and patients [25][26][27][27][28]. Breast cancer screening with the help of artificial intelligence has been successfully implemented. Multi-center studies indicate that there are improved rates of detection, lower rates of false negatives, and reading time is reduced by up to 91%, including cancers that radiologists did not identify [29]. These will help in better training of clinicians, standardize results, and reduce shortages in the workforce.

Deep learning algorithms sometimes outperform radiologists' diagnosis of breast and lung cancer. In open-access platforms, tumor localization and differentiation between malignant and non-malignant are made possible. In the field of digital pathology, artificial intelligence reduces inter-observer differences and enhances the processing capacity. Using the combination of imaging features, laboratory testing, and clinical records, artificial intelligence enables the prediction of risk in chronic conditions, such as cardiovascular disease and diabetes. Risk stratification at early stages enables such interventions to be personalized, thus improving patient outcomes. Instantaneous alerts are beneficial to intensive-care-unit monitoring, but conversational agents enhance the diagnostic process. Failure to produce the expected effect empirically highlights the lack of generalization, lack of integration, and lack

of adequate training. The mitigation requires tedious validation, human-focused design, and continuous audit procedures.

The clinicians consider model interpretability and flexibility to be the most important; the explainability of explainable artificial intelligence encourages trust, and those models that are not transparent evoke distrust. Human interaction, privacy, and reduced human interaction are the concerns expressed by patients. The human-in-the-loop systems maintain the supervisory power; hence, the balance of efficacy and empathic care [30].

$$\Delta\text{Accuracy} = \beta 0 + \beta 1 \times \text{AI Adoption Level} + \epsilon \qquad (11)$$

Equation (11) models diagnostic accuracy gains as a function of AI adoption intensity. Algorithms' bias and fairness were covered in 20 out of 30 studies (67%), and thus, it is the most common ethical issue. Explainability and transparency were mentioned in 18 studies (60%), and data privacy and security were mentioned in 17 studies (57%). In 14 studies (47%), Accountability and legal liability were increased. These allocations underscore the fact that the literature is dominated by technical ethical issues, whereas governance and the implementation of policies have been relatively under-researched.

Results:

This section will outline the most meaningful tendencies, existing ethical concerns, gaps in the research, and gaps in governance that were identified in the analyzed literature on artificial intelligence in diagnostic medicine. The findings are divided into three categories of themes that represent the most stable and most relevant findings of studies. As Table 1 demonstrates, various AI diagnostic areas come with unique ethical threats and governance gaps, which explains the importance of regulatory and oversight solutions specific to these domains.

Dominant Ethical Themes in AI-Based Diagnostics:

Four common ethical concerns when using AI-based diagnostics have been demonstrated in the literature review. The most frequent are algorithmic bias and fairness, in which the unequal data used in training creates disparities in the diagnostic performance across demographic groups. Explainability and transparency are also critical as black-box models undermine trust in clinicians and restrict informed decision-making. The confidentiality of information is a matter of continuous concern since medical information is privacy sensitive at large. Finally, there is no clear definition of accountability and legal liability, and no consensus regarding accountability in case of diagnostic error among developers, clinicians, and institutions.

Trends and Scope in AI-Enabled Diagnostic Research:

The conceptual and policy-focused research base has grown significantly, but the percentage of investigations that focus on empirical research on real-world clinical implementation is relatively low. Ethical aspects like bias, transparency, justice, and accountability are well-addressed, and less popular are practical aspects, such as communicating with patients and sharing their diagnostic outcomes with the help of AI. In the literature, a gradual move towards interdisciplinary research is also observed with the integration of viewpoints in medicine, computer science, ethics, and health policy. Although this has been achieved to date, a significant number of studies still focus on theoretical rather than longitudinal clinical assessment, and this means that there is still a gap between concepts and practice.

Research Gaps and Governance Challenges:

Most studies lack quantitative comparisons and primary clinical evidence, while the rapid evolution of AI consistently outpaces ethical standards and regulatory frameworks. A key trade-off exists between diagnostic accuracy and model transparency: deep neural networks offer superior predictive performance, but their black-box nature erodes clinician trust, complicates accountability, and limits informed consent. XAI methods such as SHAP

and LIME offer a viable path to balance these competing demands, as illustrated in Figure 3. Clinically, the results support the use of artificial intelligence as a decision-aiding tool and not as a substitute for human judgment. Doctor-patient communication and clarity about the AI-supported decision-making are very important to uphold trust and ethical codes in medical practice.

There are also important policy and governance implications of the results. Instead of a model of approval that stays at the same level, policymakers need to shift to ongoing supervision mechanisms that include consideration of the model changes, actual performance, and the emergence of risks. The cooperation between technologists, clinicians, ethicists, and regulators is thus necessary to make sure AI-based diagnostics are implemented safely, fairly, and in accordance with the values of society.

Table 1. AI Diagnostic Domains and Associated Ethical and Governance Challenges

AI Diagnostic Domain	Common Application	Dominant Ethical Concerns	Governance & Policy Gaps
Radiology & Imaging	Cancer detection, fracture analysis, and large-scale screening	Bias in training data, lack of explainability	Limited post-deployment monitoring, unclear liability frameworks
Pathology	Histopathology image analysis, tumor grading, and classification	Transparency of model decisions, dataset representativeness	Cross-institutional validation and standardization challenges
Predictive Diagnostics	Risk stratification, disease progression prediction	Fairness, over-reliance on automated predictions	Accountability for incorrect or misleading predictions
Clinical Decision Support	Treatment recommendations, triage, and prioritization	Explainability, clinician trust, and autonomy	Integration with existing clinical workflows and responsibility allocation
Telemedicine & Remote Monitoring	Early disease detection, wearable, and sensor-based data analysis	Privacy concerns, informed consent	Data ownership, cross-border data governance, and regulation

Future Research and Innovation:

The rapid emergence of artificial intelligence in the healthcare sector requires the corresponding enhancement of technological competencies and ethical provisions. Federated learning, differing privacy, and homomorphic encryption all fall under the category of privacy-preserving methodologies, which allow institutions to jointly learn models without necessarily sharing the raw patient data. The formal guarantees on data security are guaranteed by the use of controlled privacy budgets and randomized algorithms.

Here, M denotes the stochastic model, D and D' are neighboring datasets, ϵ is the privacy budget, and S is any output subset. Such complementary innovations as fairness-aware modeling and explainable artificial intelligence (XAI), which combine rule-driven, statistical, and visual explanatory modalities to enhance clinician confidence and adherence to regulatory specifications, are complementary innovations. Privacy AI solutions can protect patient data without being less predictive. Differential privacy adds controlled noise, and homomorphic encryption allows computation to be done on encrypted data. These methods comply with the GDPR and HIPAA rules and create a balance between the data utility and privacy.

XAI offers a rule-based algorithm, multimodal saliency mapping, and interactive visual analytics with the aim of offering clinically relevant reasoning. The predictive efficacy and interpretability balance is reached when the trust of the clinicians is established.

Equity has remained a priority; therefore, systematic bias audit and inclusive datasets are essential to prevent inequities. Global efforts are aimed at aligning ethical standards, regulatory systems, and responsibility tools, and contributing to the responsible use of AI and increasing patient trust.

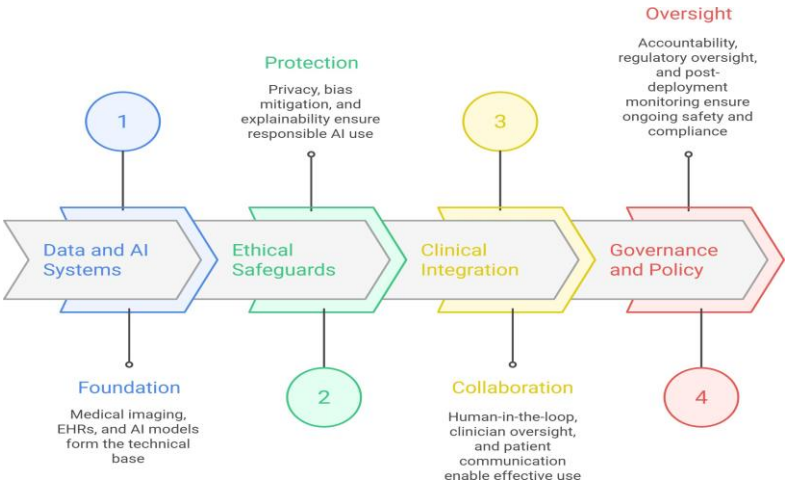


Figure 3. Ethical, Clinical, and Governance Framework for AI-based Diagnostic Systems

$$\epsilon\text{-DP: } \forall S,\ \Pr[M(D) \in S] \leq e^{\epsilon} \Pr[M(D') \in S] \quad (12)$$

Conclusions and Discussion:

Artificial intelligence has a great prospect of revolutionizing the field of diagnostic medicine by increasing its accuracy, early identification of diseases, and simplifying the clinical process. Nevertheless, these advantages will depend on effective ethical protection, strict validation, and properly organized control. The absence of transparency, algorithmic bias, and accountability has been a recurrent problem that need to be eliminated by incorporating clinical integration strategies to make AI a decision-support tool instead of a human judgment replacement. Technologists, clinicians, ethicists, and policymakers must work together in an interdisciplinary manner to develop governance structures that can keep abreast of the quickly evolving AI technologies. Equity, trust, and clinical excellence in healthcare delivery can be promoted by explainable, patient-centered, and privacy-preserving AI systems. There are limitations to this review: being a narrative review, they are prone to selection bias, have not been empirically validated primarily, and some of the frameworks reviewed might have advanced since the time of writing. Longitudinal clinical research and empirical governance evaluations in various healthcare contexts should be given priority in future work.

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