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Artificial Intelligence in Brazilian medical practice: Clinical integration, governance challenges, and strategic perspectives

Inteligência Artificial na prática médica brasileira: Integração clínica, desafios de governança e perspectivas estratégicas

Inteligencia Artificial en la práctica médica brasileña: Integración clínica, desafíos de gobernanza y perspectivas estratégicas

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Abstract
Artificial Intelligence (AI) has progressively expanded from experimental applications to clinically relevant performance across multiple medical domains. This integrative review analyzes current applications of AI in Brazilian medical practice, with emphasis on clinical integration, governance challenges, and strategic perspectives. A structured search of PubMed, SciELO, and Google Scholar was conducted covering publications from 2018 to 2025. A total of 127 studies were included in the qualitative synthesis, and 20 high-impact studies were selected for in-depth thematic analysis. Results indicate consolidated diagnostic performance in imaging-based specialties and predictive modeling, while highlighting persistent gaps in external validation, real-world implementation, and equitable deployment. Recent developments in generative AI introduce additional regulatory and safety complexities, particularly regarding dynamic validation and post-deployment monitoring. In Brazil, AI integration occurs within a universal healthcare system marked by infrastructural heterogeneity and evolving regulatory frameworks, including the General Data Protection Law and the National Digital Health Strategy. The findings suggest that sustainable AI integration depends not solely on algorithmic sophistication but on governance maturity, institutional readiness, and equitable health system strengthening.
Keywords: Artificial Intelligence; Medical practice; Brazil; Health governance; Digital health.

Resumo
A Inteligência Artificial (IA) tem avançado de aplicações experimentais para desempenho clinicamente relevante em múltiplos domínios médicos. Esta revisão integrativa analisa as aplicações atuais da IA na prática médica brasileira, com ênfase na integração clínica, nos desafios de governança e nas perspectivas estratégicas. Foi realizada busca estruturada nas bases PubMed, SciELO e Google Scholar, abrangendo publicações de 2018 a 2025. Um total de 127 estudos foi incluído na síntese qualitativa, sendo 20 selecionados para análise temática aprofundada. Os resultados demonstram desempenho diagnóstico consolidado em especialidades baseadas em imagem e em modelos preditivos, ao mesmo tempo em que evidenciam lacunas persistentes na validação externa, na implementação em contexto real e na implantação equitativa. O avanço recente da IA generativa acrescenta complexidades regulatórias e de segurança, especialmente quanto à validação dinâmica e ao monitoramento pós-implantação. No Brasil, a incorporação da IA ocorre em um sistema universal de saúde marcado por heterogeneidade estrutural e arcabouço regulatório em evolução, incluindo a Lei Geral de Proteção de Dados e a Estratégia de Saúde Digital. Conclui-se que a integração sustentável da IA depende não apenas da sofisticação algorítmica, mas da maturidade de governança e da preparação institucional.
Palavras-chave: Inteligência Artificial; Prática médica; Brasil; Governança em saúde; Saúde digital.

Resumen
La Inteligencia Artificial (IA) ha evolucionado desde aplicaciones experimentales hacia un desempeño clínicamente relevante en múltiples dominios médicos. Esta revisión integrativa analiza las aplicaciones actuales de la IA en la práctica médica brasileña, con énfasis en la integración clínica, los desafíos de gobernanza y las perspectivas estratégicas. Se realizó una búsqueda estructurada en PubMed, SciELO y Google Scholar, incluyendo publicaciones entre 2018 y 2025. Se incluyeron 127 estudios en la síntesis cualitativa y 20 fueron seleccionados para análisis temático en profundidad. Los resultados evidencian un desempeño diagnóstico consolidado en especialidades basadas en imágenes y modelos predictivos, al tiempo que señalan brechas persistentes en validación externa, implementación

en contextos reales y despliegue equitativo. El desarrollo reciente de la IA generativa introduce nuevas complejidades regulatorias y de seguridad, especialmente en relación con la validación dinámica y la supervisión posterior a la implementación. En Brasil, la integración de la IA ocurre dentro de un sistema universal de salud caracterizado por heterogeneidad estructural y marcos regulatorios en evolución. La integración sostenible de la IA depende no solo de la sofisticación algorítmica, sino también de la madurez de gobernanza y la preparación institucional.
Palabras clave: Inteligencia Artificial; Práctica médica; Brasil; Gobernanza en salud; Salud digital.

1. Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technological developments in contemporary medicine, particularly following the consolidation of machine learning and deep learning applications in clinical environments after 2018 (Topol, 2019; Rajpurkar et al., 2022). Advances in computational capacity, availability of large-scale health datasets, and algorithmic refinement have enabled AI systems to perform complex diagnostic and predictive tasks with increasing accuracy across multiple medical specialties.

Robust validation studies have demonstrated high diagnostic performance in imaging-intensive fields such as radiology and pathology. Multinational evaluations of AI systems for breast cancer screening and digital pathology have reported reductions in false-positive and false-negative rates, approaching or exceeding specialist-level performance in controlled settings (Campanella et al., 2019; McKinney et al., 2020). Systematic reviews and meta-analyses further indicate pooled sensitivities and specificities frequently above 85%, although heterogeneity and limited external validation remain persistent concerns (Liu et al., 2019). These findings highlight both the clinical potential and the methodological challenges inherent in AI translation to routine care.

Beyond diagnostic imaging, predictive modeling has demonstrated promise in critical care and risk stratification scenarios. Machine learning models for sepsis prediction and population health management illustrate the capacity of AI to enhance early warning systems and optimize resource allocation (Nemati et al., 2018; Rajkomar et al., 2019). However, large-scale implementation analyses have revealed a consistent gap between algorithmic performance and real-world clinical impact, emphasizing the importance of workflow integration, human oversight, and system readiness (Kelly et al., 2019; Wiens et al., 2019).

In recent years, generative AI and large language models (LLMs) have expanded the scope of AI applications in healthcare, including clinical reasoning support, documentation assistance, and medical education. Meta-analytic evidence from 2025 suggests that generative AI models demonstrate promising diagnostic capabilities, yet concerns persist regarding hallucinations, safety, and reproducibility (Takita et al., 2025). Similarly, emerging frameworks for dynamic evaluation of AI systems argue that traditional static validation models may be insufficient for continuously evolving algorithms, reinforcing the need for adaptive clinical trial methodologies (Rosenthal et al., 2025). These developments underscore the accelerating pace of innovation while intensifying regulatory and governance challenges.

The global debate on AI governance has become increasingly prominent. International regulatory guidance emphasizes transparency, accountability, explainability, and risk-based oversight as essential pillars for trustworthy AI deployment (European Commission, 2019; World Health Organization, 2021). High-profile analyses have also demonstrated that algorithmic bias may inadvertently reinforce health inequities when training data reflect structural disparities (Obermeyer et al., 2019). In 2025, renewed discussions in leading medical forums have stressed the urgency of establishing credible evidence standards to sustain public trust and ensure safe integration of AI technologies into healthcare systems (Angus, 2025; Lancet Digital Health, 2025).

In Brazil, AI integration into medical practice occurs within the structural complexity of a universal healthcare system characterized by regional disparities in infrastructure and digital maturity. While tertiary academic centers and private institutions have progressively adopted AI-supported diagnostic tools, large-scale implementation within the Unified Health System (Sistema Único de Saúde – SUS) remains heterogeneous. National digital transformation initiatives have advanced through the Brazilian Digital Health Strategy (2020–2028), yet implementation depends on regulatory clarity, data governance, and workforce preparedness (Brasil, Ministério da Saúde, 2020; Massuda et al., 2018). Moreover, the Brazilian General Data Protection Law (Lei nº 13.709/2018 – LGPD) establishes a comprehensive legal framework for sensitive health data processing, directly impacting AI system development and deployment (Brasil, 2018).

Given the rapid evolution of AI technologies, the expansion of generative models, and the increasing regulatory scrutiny worldwide, a structured and updated evaluation of AI applications in Brazilian medical practice is warranted. Understanding how global evidence intersects with national governance structures is essential to ensure safe, equitable, and sustainable implementation.

Objective**.** This study aims to analyze current applications of Artificial Intelligence in Brazilian medical practice, discuss regulatory and ethical challenges, and explore future perspectives within the national healthcare context.

2. Methodology

2.1 Study Design

This study was conducted as a documentary integrative literature review, structured according to established methodological frameworks for integrative synthesis (Snyder, 2019; Whittemore & Knafl, 2005; Crossetti, 2012). Integrative reviews allow the inclusion of empirical studies with diverse methodological designs, as well as institutional and regulatory documents, enabling comprehensive analysis of emerging and interdisciplinary topics.

The review adopted a quantitative approach regarding the number of studies identified, screened, and included in the corpus, and a qualitative analytical approach in relation to thematic interpretation and synthesis of findings (Pereira et al., 2018). Reporting transparency was guided by PRISMA 2020 principles (Page et al., 2021).

2.2 Research Question

The guiding question of this review was:

How has Artificial Intelligence been applied in medical practice, and what are the principal regulatory and ethical challenges for its implementation in Brazil?

The review incorporated global evidence while emphasizing interpretative implications for the Brazilian healthcare system.

2.3 Data Sources And Search Strategy

A structured search was conducted in PubMed/MEDLINE, SciELO, and Google Scholar, covering publications from January 1, 2018 to December 31, 2025.

The starting year (2018) was selected due to the consolidation of deep learning architectures and the acceleration of AI implementation in healthcare systems during this period (Topol, 2019).

Search terms included combinations of controlled vocabulary and free-text expressions:

- “artificial intelligence”
- “machine learning”
- “deep learning”
- “generative AI”

- “large language models”
- “medical practice”
- “healthcare”
- “clinical decision support”
- “Brazil”
- “regulation”
- “ethics”
- “data protection”
- “LGPD”

Boolean operators (AND/OR) were applied. An example PubMed search strategy was:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "generative AI") AND ("medical practice" OR "healthcare" OR "clinical decision support") AND (Brazil OR regulation OR ethics OR "data protection").

For Google Scholar, results were sorted by relevance and the first 200 records were screened to enhance reproducibility.

Institutional and regulatory documents were identified through targeted searches of official governmental and international health organization websites, including the Brazilian Digital Health Strategy (2020–2028), the Brazilian General Data Protection Law (LGPD), and international governance guidelines (Brasil, 2018; Brasil, Ministério da Saúde, 2020; World Health Organization, 2021; European Commission, 2019).

2.4 Eligibility Criteria

Inclusion criteria:

- Peer-reviewed original studies, systematic reviews, meta-analyses, and high-impact perspective articles addressing AI in healthcare;
- Studies involving clinical, operational, educational, or governance applications of AI;
- Institutional and regulatory documents relevant to AI governance in healthcare;
- Publications in English, Portuguese, or Spanish;
- Full-text availability;
- Publication between 2018 and 2025.
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Exclusion criteria:

- Publications prior to 2018;
- Duplicate records;
- Studies without clinical or health system relevance;
- Purely technical computational studies without healthcare implementation implications;
- Opinion Pieces Lacking Methodological Or Institutional Grounding.
-

2.5 Study Selection Process

All identified records were exported to a reference management system and screened in two stages:

1. Title and abstract screening;

2. Full-text eligibility assessment.

Duplicates were removed prior to screening. The selection process followed PRISMA 2020 transparency recommendations (Page et al., 2021).

The distribution of records across identification, screening, eligibility, and inclusion stages is presented in Table 1.

Table 1 - *Study selection process according to PRISMA 2020 framework.*

Stage	Records (n)	Description
Identification	248	Records identified through database searching (PubMed, SciELO, Google Scholar)
Additional sources	23	Institutional and regulatory documents identified through targeted search
Total records identified	271	Total records before duplicate removal
Duplicates removed	36	Records removed prior to screening
Records screened	235	Titles and abstracts assessed for eligibility
Records excluded	82	Excluded for irrelevance or failure to meet inclusion criteria
Full-text articles assessed	153	Full-text articles evaluated for eligibility
Full-text articles excluded	26	Excluded due to methodological limitations or lack of clinical relevance
Studies included in qualitative synthesis	127	Final corpus included for thematic analysis
Core studies selected for in-depth analysis	20	High-impact and representative studies included in Table 2

Source: Authors.

2.6 Data Extraction And Synthesis

A standardized extraction framework was applied to eligible studies, capturing:

- Author and year
- Study design
- Country or setting
- AI methodology
- Clinical or operational domain
- Reported performance metrics
- Validation characteristics
- Ethical or regulatory considerations

Thematic domains were defined a priori:

1. Clinical diagnostic applications
2. Predictive modeling and risk stratification
3. Generative AI and large language models
4. Health system operations and workflow optimization
5. Regulatory, ethical, and governance challenges

Narrative synthesis emphasized implementation feasibility, external validation robustness, reproducibility, bias, and governance maturity.

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2.7 Selection Of Core Studies For In-Depth Analysis

From the total corpus of studies included in the qualitative synthesis, a subset of 20 high-impact and methodologically representative studies was selected for in-depth thematic analysis.

Selection criteria prioritized:

1. External validation studies or high-impact empirical investigations;
2. Systematic reviews and meta-analyses;
3. Recent publications (including 2025 studies addressing generative AI and dynamic validation frameworks);
4. Institutional and regulatory documents with direct governance relevance.

These 20 core studies are presented in Table 2 and structured the analytical development of the Results and Discussion sections.

Table 2 - *Core studies included for in-depth analysis in the integrative review.*

A. Clinical performance and external validation

Author (Year)	Scope	Study Design	AI Domain	Key Findings	Relevance to Brazilian Context
Campanella et al. (2019)	USA	Multicenter retrospective study	Digital pathology	Achieved clinical-grade performance in histopathology	Relevant for tertiary and academic Brazilian centers
McKinney et al. (2020)	Multinational	External validation study	Breast cancer screening	Reduced false positives and false negatives compared to radiologists	Highlights need for external validation before national deployment
Liu et al. (2019)	Global	Systematic review and meta-analysis	Diagnostic imaging AI	Pooled sensitivity and specificity frequently >85%; high heterogeneity	Emphasizes validation and reproducibility challenges
Nemati et al. (2018)	USA	Predictive modeling study	Sepsis prediction	Improved early-warning performance compared to traditional scores	Potential application in emergency settings within SUS
Rajkomar et al. (2019)	USA	Perspective article	Machine learning in medicine	Broad applicability of ML for diagnosis and risk prediction	Supports predictive modeling and decision-support systems

B. Implementation and translational challenges

Author (Year)	Scope	Study Design	AI Domain	Key Findings	Relevance to Brazilian Context
Kelly et al. (2019)	UK	Implementation analysis	AI translation to practice	Identified gap between algorithm performance and real-world impact	Reinforces implementation barriers in Brazil
Sendak et al. (2020)	USA	Translational framework analysis	Clinical ML deployment	Proposed structured pathway for safe translation of ML models into healthcare systems	Highly relevant for operational implementation in SUS
Wiens et al. (2019)	Global	Roadmap article	Responsible machine learning	Proposed structured framework for safe AI implementation	Governance reference applicable to Brazilian regulation

C. Generative AI and emerging models

Author (Year)	Scope	Study Design	AI Domain	Key Findings	Relevance to Brazilian Context
Kung et al. (2023)	USA	Evaluation study	Generative AI (ChatGPT)	Demonstrated performance on USMLE-style questions	Illustrates emerging impact of LLMs in medical education
Takita et al. (2025)	Global	Systematic review and meta-analysis	Generative AI diagnostics	Promising diagnostic accuracy; concerns about safety and hallucinations	Strengthens discussion on generative AI regulation

Author (Year)	Scope	Study Design	AI Domain	Key Findings	Relevance to Brazilian Context
Rosenthal et al. (2025)	Global	Methodological framework study	Clinical AI trials	Proposed dynamic deployment and adaptive validation models	Relevant for future regulatory frameworks in Brazil
Angus (2025)	USA	Editorial / Policy analysis	AI governance in healthcare	Emphasized need for credible evidence standards and oversight	Reinforces governance urgency in emerging systems
Lancet Digital Health (2025)	Global	Policy analysis	Evidence standards for medical AI	Highlighted need for trust, transparency, and robust validation	Comparative governance benchmark for Brazil

D. Bias, ethics, and professional transformation

Author (Year)	Scope	Study Design	AI Domain	Key Findings	Relevance to Brazilian Context
Obermeyer et al. (2019)	USA	Retrospective cohort analysis	Algorithmic bias	Identified racial bias in widely used population health algorithm	Critical for addressing socioeconomic disparities in Brazil
Topol (2019)	Global	Perspective article	Clinical AI integration	AI augments rather than replaces clinicians	Frames debate on augmentation vs substitution within SUS
Wartman & Combs (2019)	USA	Educational review	AI in medical education	Advocated curricular reform and AI literacy integration	Supports discussion on national educational gaps

E. Governance and regulatory frameworks

Author (Year)	Scope	Study Design	AI Domain	Key Findings	Relevance to Brazilian Context
World Health Organization (2021)	Global	Institutional guideline	AI ethics and governance	Defined transparency, accountability, and human oversight principles	Normative international reference
European Commission (2019)	European Union	Regulatory framework	Trustworthy AI	Risk-based regulatory classification model	Comparative framework for Brazilian policy evolution
Brasil (2018) – LGPD	Brazil	Federal legislation	Data protection	Regulates processing of sensitive personal health data	Foundational legal basis for AI deployment in Brazil
Brasil, Ministério da Saúde (2020)	Brazil	National policy document	Digital health strategy	Established national roadmap for digital transformation	Institutional readiness and infrastructure context

Source: Authors.

2.8 Selection of Core Studies For In-Depth Analysis

From the total corpus of studies included in the qualitative synthesis, a subset of 20 high-impact and methodologically representative studies was selected for in-depth thematic analysis.

Selection criteria prioritized:

1. External validation studies or high-impact empirical investigations;
2. Systematic reviews and meta-analyses;
3. Recent publications (including 2025 studies addressing generative AI and dynamic validation frameworks);
4. Institutional and regulatory documents with direct governance relevance.

These 20 core studies are presented in Table 2 and structured the analytical development of the Results and Discussion sections.

2.9 Quality Appraisal

Methodological quality was appraised using design-appropriate frameworks. The JBI Manual for Evidence Synthesis informed interpretative rigor (Aromataris & Munn, 2020). For mixed-methods studies, the Mixed Methods Appraisal Tool (MMAT) was consulted when applicable (Hong et al., 2018).

Appraisal results informed interpretation but were not used as exclusion criteria.

2.10 Ethical Considerations

This review analyzed publicly available literature and institutional documents. No individual-level patient data were collected. Therefore, institutional ethical approval was not required.

3. Results

3.1 Study Selection

The database search identified 271 records, including peer-reviewed publications and institutional documents. After removal of 36 duplicates, 235 records underwent title and abstract screening. Eighty-two records were excluded for lack of relevance to clinical application, governance implications, or healthcare implementation of Artificial Intelligence (AI).

Full-text assessment was conducted on 153 articles. Twenty-six studies were excluded due to insufficient methodological transparency, absence of healthcare applicability, or purely technical focus without clinical or system-level implications. Ultimately, 127 studies were included in the qualitative synthesis.

From this corpus, 20 high-impact and methodologically representative studies were selected for structured thematic analysis according to predefined criteria of validation robustness, implementation relevance, recency, and regulatory significance. The study selection process is presented in Table 1, and the selected core studies are detailed in Table 2.

3.2 Distribution Of Studies By Thematic Domain

Among the 127 studies included in the qualitative synthesis:

- Approximately 38% addressed diagnostic performance in imaging-based specialties or pathology;
- 21% focused on predictive modeling and risk stratification;
- 14% examined implementation and translational challenges;
- 11% discussed generative AI and large language models;
- 16% analyzed regulatory, ethical, and governance dimensions.

This distribution reflects the predominance of performance-driven research in the field, while governance and implementation dimensions remain comparatively less represented in the literature.

3.3 Clinical Performance And External Validation

The largest proportion of studies examined diagnostic accuracy in radiology and pathology. Multicenter and multinational investigations demonstrated that AI systems can achieve clinical-grade performance under controlled conditions, particularly in breast cancer screening and computational pathology (Campanella et al., 2019; McKinney et al., 2020).

Meta-analytic evidence reported pooled sensitivity and specificity frequently exceeding 85% in imaging tasks, though with substantial heterogeneity and limited external validation across diverse populations (Liu et al., 2019). Predictive modeling studies similarly demonstrated improved early detection capabilities in acute conditions such as sepsis (Nemati et al., 2018), while broader analyses highlighted the general applicability of machine learning models for diagnosis and prognosis (Rajkomar et al., 2019).

However, recurrent methodological limitations included dataset homogeneity, limited representation of low- and middle-income contexts, and insufficient prospective validation. These constraints are particularly relevant when considering large-scale deployment in heterogeneous healthcare systems.

3.4 Implementation And Translational Challenges

Seventeen percent of the analyzed corpus addressed implementation barriers. High-performing models frequently failed to demonstrate equivalent impact in real-world clinical settings. Implementation analyses emphasized that algorithmic accuracy alone does not ensure clinical adoption (Kelly et al., 2019).

Structured translational frameworks proposed multidisciplinary integration, continuous monitoring, and governance oversight as prerequisites for sustainable deployment (Sendak et al., 2020; Wiens et al., 2019). The literature consistently underscored that infrastructural readiness, interoperability of health information systems, and clinician engagement are decisive determinants of AI success.

In contexts characterized by regional disparities in digital infrastructure, such as Brazil, these findings highlight potential scalability limitations.

3.5 Generative Ai And Emerging Models

Generative AI constituted one of the fastest-growing thematic domains, particularly from 2023 onward. Evaluation studies demonstrated that large language models achieved performance comparable to medical trainees in standardized examinations (Kung et al., 2023).

Recent meta-analytic evidence published in 2025 suggests promising diagnostic accuracy across selected tasks, although concerns persist regarding hallucination rates, factual inconsistencies, and reliability under unsupervised clinical use (Takita et al., 2025). Furthermore, emerging methodological frameworks advocate dynamic deployment models and adaptive validation strategies, arguing that static validation paradigms are insufficient for continuously evolving AI systems (Rosenthal et al., 2025).

Policy-level discussions published in 2025 emphasized the necessity of establishing robust evidence standards and structured post-deployment surveillance mechanisms to preserve public trust (Angus, 2025; Lancet Digital Health, 2025).

3.6 Bias, Ethics, And Governance

Ethical and governance concerns represented 16% of the included literature. Retrospective cohort analyses demonstrated that widely implemented health algorithms may reproduce racial and socioeconomic disparities when trained on biased datasets (Obermeyer et al., 2019).

The literature emphasized that AI systems should function as tools to augment, rather than replace, human clinical reasoning (Topol, 2019). Additionally, integration of AI literacy into medical education was identified as a critical component for safe implementation (Wartman & Combs, 2019).

International governance frameworks consistently identified transparency, accountability, explainability, and human oversight as foundational principles (World Health Organization, 2021; European Commission, 2019). Within Brazil, the General Data Protection Law (LGPD) and the National Digital Health Strategy provide regulatory and institutional scaffolding for AI integration, although operationalization remains uneven across regions (Brasil, 2018; Brasil, Ministério da Saúde, 2020).

4. Discussion

The present integrative review demonstrates that Artificial Intelligence (AI) in healthcare has reached a stage of consolidated diagnostic performance in controlled environments, yet continues to face significant translational and governance barriers in real-world implementation. While high levels of sensitivity and specificity have been consistently reported in imaging-based specialties and predictive modeling applications (Campanella et al., 2019; Liu et al., 2019; McKinney et al., 2020), the literature simultaneously highlights persistent challenges related to external validation, reproducibility, and equitable deployment (Kelly et al., 2019; Wiens et al., 2019).

A central finding across domains is the discrepancy between algorithmic accuracy and clinical impact. Many systems demonstrate promising results under retrospective or controlled validation conditions but encounter difficulties when integrated into heterogeneous healthcare environments. This translational gap is not merely technical; it reflects organizational readiness, data interoperability, workflow redesign, and professional acceptance (Sendak et al., 2020). In universal healthcare systems characterized by infrastructural disparities, such as Brazil's Unified Health System (SUS), these challenges may be amplified.

The emergence of generative AI and large language models introduces additional complexity. While recent evidence suggests promising diagnostic and reasoning capabilities (Kung et al., 2023; Takita et al., 2025), the dynamic nature of these systems challenges traditional regulatory models. Adaptive validation frameworks have been proposed to address continuous model evolution (Rosenthal et al., 2025), yet consensus regarding post-deployment monitoring remains limited. Policy analyses emphasize that trust in medical AI depends on transparent evidence standards and rigorous oversight (Angus, 2025; Lancet Digital Health, 2025).

Ethical and equity considerations constitute another critical dimension. The identification of algorithmic bias in widely implemented healthcare tools underscores the risk of perpetuating structural inequities (Obermeyer et al., 2019). In Brazil, where regional socioeconomic disparities are substantial, the potential amplification of inequities through poorly validated AI systems represents a significant concern. Ethical deployment therefore requires not only compliance with data protection legislation such as the LGPD (Brasil, 2018), but also proactive auditing of fairness and representativeness in training datasets.

International governance frameworks consistently advocate transparency, accountability, explainability, and human oversight as foundational principles for trustworthy AI (World Health Organization, 2021; European Commission, 2019). However, translating these principles into enforceable regulatory mechanisms remains an ongoing global challenge. In Brazil, the Digital Health Strategy (2020–2028) provides institutional direction, yet operational implementation depends on coordinated investment in digital infrastructure, workforce training, and regulatory clarity (Brasil, Ministério da Saúde, 2020; Massuda et al., 2018).

Importantly, the predominance of performance-driven research identified in this review suggests that the field remains disproportionately focused on algorithm development rather than system-level integration. Future research should prioritize prospective validation studies, real-world effectiveness trials, and implementation science frameworks capable of evaluating long-term clinical and economic outcomes.

This review has limitations. As an integrative review, it synthesizes heterogeneous evidence and does not provide pooled quantitative estimates beyond those reported in included meta-analyses. Additionally, although global evidence was incorporated to contextualize technological evolution, the Brazilian literature remains comparatively limited, reflecting the early stage of structured national AI implementation research.

Despite these limitations, the findings highlight that AI integration in Brazilian medical practice is not primarily constrained by algorithmic capability, but by governance maturity, infrastructural heterogeneity, and translational readiness.

The trajectory of AI in Brazil will likely depend on the alignment between technological innovation, regulatory frameworks, and equitable health system strengthening.

5. Conclusion

Artificial Intelligence in healthcare has progressed from experimental application to clinically relevant performance in multiple domains, particularly in imaging-based diagnostics and predictive modeling. However, evidence synthesized in this review demonstrates that technological capability alone does not guarantee safe, equitable, or scalable implementation.

In the Brazilian context, the integration of AI into medical practice is shaped by structural heterogeneity, regulatory evolution, and institutional readiness. While national frameworks such as the General Data Protection Law (LGPD) and the Digital Health Strategy provide foundational governance structures, operational translation depends on infrastructure strengthening, workforce training, and the establishment of robust validation and oversight mechanisms.

The emergence of generative AI further intensifies the need for adaptive regulatory models capable of addressing continuously evolving systems. Ensuring transparency, accountability, and equitable deployment will be central to sustaining public trust and maximizing clinical benefit.

Ultimately, the future of AI in Brazilian medical practice will not be determined solely by algorithmic sophistication, but by the alignment between innovation, governance maturity, and health system resilience.

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