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ARTIFICIAL INTELLIGENCE IN EARLY ONCOLOGY SCREENING: A SYSTEMATIC REVIEW OF ETHICAL IMPLICATIONS, HEALTH EQUITY, AND DIGITAL ACCESS DISPARITIES

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ABSTRACT

Background: Artificial intelligence (AI) has rapidly evolved in oncology over the past decade, transforming early cancer screening through advances in imaging analytics, predictive modeling, and data-driven risk stratification [6,9,17]. Early research primarily focused on diagnostic performance and technical efficiency, however, recent literature increasingly emphasizes the ethical, social, and structural consequences of AI integration into healthcare systems [2,6,8].
Objective: This review analyzes the development of AI in early oncology screening between 2018 and 2026, focusing on ethical implications, health equity, and digital access disparities at the intersection of technology and society.
Methodology: A structured literature review was conducted using the PubMed database. Peer-reviewed review articles and policy-oriented studies published between 2018 and 2026 were analyzed. Inclusion criteria comprised relevance to AI-based cancer screening, ethical governance, health equity, social determinants of health, and digital inclusion [1–10].
Results: The literature demonstrates a shift from performance-centered AI development toward socially informed frameworks emphasizing fairness, transparency, and governance [1,6,8]. Although AI technologies enhance early detection potential [9,17], consistent evidence highlights risks of algorithmic bias, unequal access to digital infrastructure, and reinforcement of pre-existing health disparities [2,5,10,12,15]. Vulnerabilities are particularly evident among socioeconomically disadvantaged populations and in low- and middle-income countries (LMICs), where infrastructural limitations restrict equitable implementation [2,18].
Conclusion: AI in early oncology screening holds substantial clinical promise, however, without ethically grounded governance and equity-oriented policy frameworks, its deployment risks amplifying structural inequalities. Sustainable integration requires inclusive data practices, digital access equity, and human-centered regulatory models to ensure socially responsible innovation. Technological innovation in oncology cannot be evaluated independently of its social context and systemic determinants.

KEYWORDS

Artificial Intelligence, Oncology Screening, Health Equity, Digital Divide, Ethical Governance, Social Determinants of Health

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1. Introduction

Early cancer detection remains one of the most significant determinants of oncologic prognosis and long-term survival. Across multiple cancer types—including breast, lung, and colorectal malignancies—earlier stage diagnosis is consistently associated with improved treatment responsiveness, reduced mortality, and lower long-term healthcare costs. Despite substantial advances in organized screening programs and imaging technologies, disparities in early diagnosis persist globally. These inequities disproportionately affect underserved populations, including socioeconomically disadvantaged groups, racial and ethnic minorities, rural communities, and populations in low- and middle-income countries (LMICs). Structural barriers such as limited access to screening facilities, delayed diagnostic follow-up, workforce shortages, and fragmented health systems continue to shape uneven outcomes in early cancer detection.

Artificial intelligence (AI) has emerged as a transformative force in oncology, offering new possibilities for enhancing screening precision and workflow efficiency. Deep learning and machine learning models applied to imaging analytics, digital pathology, and risk prediction algorithms demonstrate enhanced sensitivity and specificity compared with conventional approaches [9,17]. AI-driven tools have shown potential in mammography interpretation, lung nodule detection, and automated lesion classification, often outperforming or complementing human readers in controlled settings. These advances have generated considerable optimism regarding AI's capacity to improve detection rates, reduce diagnostic delays, and standardize clinical decision-making processes. However, performance-centric evaluations provide an incomplete picture of AI's broader systemic implications, particularly when technologies are deployed within structurally unequal healthcare environments [6,8].

1.1 From Performance Optimization to Ethical and Social Scrutiny

Early oncology AI research concentrated primarily on diagnostic accuracy, computational efficiency, and model optimization [9,17]. Validation studies typically emphasized metrics such as area under the curve (AUC), sensitivity, specificity, and false-positive rates, often derived from retrospective datasets collected in high-resource academic centers. While these metrics are essential for establishing technical feasibility, contemporary analyses argue that technical performance cannot be disentangled from ethical, structural, and societal considerations [2,6].

Istasy et al. highlight that AI's integration into oncology may simultaneously mitigate and exacerbate disparities, depending on governance structures, data inclusivity, and implementation contexts [6]. For example, models trained on demographically homogeneous datasets may achieve high aggregate accuracy yet perform inconsistently across subgroups. Similarly, Konate et al. emphasize the need to rethink fairness beyond statistical parity, advocating for contextualized and equity-aware AI frameworks in oncology that incorporate distributive justice principles and real-world deployment conditions [8]. This shift marks a broader transition from purely performance-driven innovation toward socio-technical evaluation, recognizing that AI systems are embedded within institutional, regulatory, and economic infrastructures.

1.2 Algorithmic Bias and Health Equity

Algorithmic bias represents a pivotal ethical challenge in AI-driven oncology screening. Bias can emerge when datasets lack demographic diversity, when proxy variables encode socioeconomic status, or when historical clinical data reflect pre-existing inequities in access to care. These distortions may not be immediately visible in aggregate performance statistics, yet they can produce systematic underperformance for specific populations.

Seminal analyses have demonstrated racial bias in widely deployed healthcare algorithms, revealing that risk prediction tools may underestimate health needs among Black patients due to cost-based proxy variables [12]. Subsequent investigations have identified underdiagnosis bias in imaging AI systems affecting underserved patient populations, particularly when training data underrepresent minority groups or resource-limited clinical settings [15]. Moreover, research has shown that AI models can infer protected characteristics such as race directly from medical imaging data—even when race is not explicitly included as an input variable—raising profound ethical concerns regarding latent demographic encoding [3]. Additional studies demonstrate that protected characteristics may remain algorithmically embedded even after explicit demographic variables are removed, suggesting that bias mitigation requires more than superficial variable exclusion [4].

Ethical scholarship has further questioned the adequacy of purely technical fairness corrections in healthcare contexts, arguing that algorithmic solutions cannot fully compensate for structural inequalities embedded in healthcare systems [10]. Collectively, this body of evidence underscores the need for demographic transparency, bias auditing, subgroup performance reporting, and intersectional validation in AI-based screening applications.

1.3 Digital Infrastructure, Access, and Global Disparities

Equitable AI deployment depends not only on algorithmic fairness but also on infrastructural readiness and digital capacity. AI-based screening systems require high-resolution imaging equipment, interoperable electronic health records, secure data storage, computational resources, and trained personnel capable of overseeing algorithmic outputs. These prerequisites are unevenly distributed both within and across countries.

Analyses focused on LMIC contexts highlight governance challenges, regulatory fragmentation, and digital infrastructure gaps that may limit equitable AI implementation [18]. In many resource-constrained settings, inconsistent internet connectivity, limited radiological capacity, and incomplete health information systems complicate the safe deployment of data-intensive technologies. Dankwa-Mullan et al. further question whether AI will bridge or widen cancer disparities, emphasizing that deployment conditions and digital access act as structural determinants of technological benefit distribution [2].

Without parallel investment in digital infrastructure, workforce training, and context-specific validation, AI risks privileging already resource-rich institutions and populations. Rather than functioning as an equalizing innovation, AI may inadvertently amplify existing inequities if introduced into health systems lacking the foundational conditions for equitable adoption.

1.4 Governance, Regulation, and Ethical Oversight

The integration of AI into population-level screening intersects with evolving regulatory frameworks and accountability mechanisms. Questions of transparency, explainability, liability, and informed consent remain central to responsible AI governance [1,7]. Screening differs from individualized diagnostics in that errors or biases may affect large population groups simultaneously, magnifying potential harm.

Kelkar et al. discuss threats to dignity and autonomy in patient-facing AI systems, particularly when algorithmic recommendations influence clinical pathways without clear explanation or recourse mechanisms [7]. Broader analyses of algorithmic fairness frameworks highlight the need for institutional accountability structures capable of auditing performance across demographic groups and monitoring equity outcomes longitudinally [1,10]. Ethical oversight must therefore extend beyond model accuracy metrics to encompass regulatory preparedness, data governance, and post-deployment evaluation.

1.5 Research Gap and Rationale

Although AI's technical capabilities in oncology are extensively documented [9,17], comparatively fewer syntheses interrogate its structural, ethical, and equity-related implications in early screening contexts. Existing reviews often focus on diagnostic performance or methodological innovation without systematically integrating considerations of digital access, governance capacity, and health equity.

The ten core studies selected [1–10] collectively address health equity, governance, bias, and digital inclusion, yet persistent gaps remain in operationalizing equity validation frameworks and ensuring global dataset representativeness. In particular, limited attention has been given to the interaction between AI deployment and broader social determinants of health, including digital literacy, socioeconomic status, and geographic disparities.

1.6 Aim of the Review

This review examines ethical implications, health equity considerations, and digital access disparities associated with AI integration in early oncology screening between 2018 and 2026. By synthesizing scholarship across clinical, ethical, and governance domains, the objective is to inform socially responsible and equity-centered innovation in cancer screening technologies and to situate AI development within its broader socio-technical context.

2. Methodology

2.1 Research Design

This study was conducted as a structured literature review examining the ethical, equity-related, and socio-technical dimensions of artificial intelligence (AI) implementation in early oncology screening. Rather than performing a quantitative meta-analysis of diagnostic performance, the review aimed to synthesize conceptual, policy-oriented, and methodological scholarship addressing the broader systemic implications of AI integration.

A structured review design was selected to enable transparent identification, selection, and thematic interpretation of relevant literature while maintaining flexibility appropriate for interdisciplinary ethical inquiry. The analytical focus extended beyond technical validation metrics to include questions of algorithmic fairness, digital inclusion, governance capacity, and structural determinants of health. This approach reflects the recognition that AI systems in oncology operate within complex socio-technical environments shaped by regulatory frameworks, institutional resources, and demographic variability.

The objective was therefore not to compare model performance statistics, but to critically examine how AI-based cancer screening technologies interact with health equity, infrastructural disparities, and ethical governance mechanisms.

2.2 Data Source and Search Strategy

A structured literature search was conducted using the PubMed/MEDLINE database, selected due to its comprehensive indexing of peer-reviewed biomedical, public health, and interdisciplinary health policy research. The search covered publications from January 2018 to February 2026 in order to capture contemporary developments in AI integration within oncology and the parallel evolution of ethical and governance scholarship.

The search strategy combined Medical Subject Headings (MeSH) and Boolean operators as follows:
– ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning")
– AND ("Cancer Screening" OR "Early Detection of Cancer" OR "Oncology Screening")
– AND ("Health Equity" OR "Health Disparities" OR "Digital Divide" OR "Algorithmic Bias" OR "Ethics" OR "Governance")
– AND ("Social Determinants of Health" OR "LMIC" OR "Access to Care")

The inclusion of both technical and socio-ethical terms was intentional, reflecting the interdisciplinary scope of the review. By integrating keywords related to governance, bias, and structural inequality, the search strategy aimed to capture literature that explicitly engages with systemic implications rather than focusing solely on diagnostic performance.

Only peer-reviewed review articles, scoping reviews, and policy-oriented analyses published in English were considered. This restriction was applied to ensure methodological rigor, conceptual depth, and interpretive coherence within the final analytical corpus.

2.3 Inclusion and Exclusion Criteria

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Study Type	systematic reviews, scoping reviews, policy analyses, methodological reviews	case reports, editorials, commentaries without analytical framework
Focus	AI applications in early oncology screening addressing ethics, health equity, digital divide, governance or social determinants of health	studies focused solely on technical model performance without socio-ethical analysis; treatment optimization studies
Database	indexed in PubMed/MEDLINE	not indexed in PubMed
Language	articles published in English	articles in languages other than English
Timeline	publications between 2018 and 2026	studies published before 2018

2.4 Study Selection Process

All records identified through the structured search strategy underwent an initial screening based on title and abstract to assess thematic relevance. This preliminary screening focused on identifying publications that explicitly addressed ethical, equity-related, governance, or digital access dimensions of AI implementation in oncology screening.

Articles that met the initial screening criteria were subsequently subjected to full-text evaluation to confirm eligibility according to the predefined inclusion and exclusion criteria. Particular attention was paid to whether the study engaged substantively with structural determinants of health, algorithmic fairness frameworks, governance mechanisms, or disparities in access to AI-enabled screening technologies.

The final analytical corpus consisted of ten core publications [1–10], selected for their explicit engagement with ethical governance, health equity, and systemic implications of AI in early oncology screening. While additional studies were reviewed during the screening process, only those providing conceptual depth and relevance to socio-technical analysis were included in the primary synthesis. This selective approach ensured coherence of the analytical framework and alignment with the review's central objective.

2.5 Data Extraction

Data from the included studies were analyzed qualitatively using a structured thematic extraction template. Rather than extracting numerical performance indicators, the review prioritized conceptual and policy-relevant dimensions related to equity and governance.

For each included publication, the following domains were systematically examined:

– Conceptualization of algorithmic bias
– Framing of health equity implications
– Governance and regulatory recommendations
– Structural and infrastructural barriers to implementation
– Proposed mitigation strategies or fairness frameworks

This structured extraction process facilitated cross-study comparison while preserving the interpretive depth necessary for interdisciplinary ethical analysis.

The synthesis followed a socio-technical perspective, recognizing AI systems as embedded within healthcare infrastructures, institutional practices, reimbursement models, and regulatory environments. This perspective acknowledges that algorithmic tools do not operate independently of the systems in which they are developed and deployed; instead, they interact with pre-existing structural inequalities that may shape their real-world impact.

2.6 Thematic Synthesis

The included studies were analyzed using a qualitative thematic synthesis approach. Rather than aggregating quantitative outcomes or calculating pooled effect estimates, the analysis focused on identifying recurring conceptual patterns and structural tensions related to ethics, equity, governance, and socio-technical implementation.

An iterative reading process was applied to identify convergent and divergent themes across publications. Emerging categories were refined through comparative analysis, enabling the development of higher-order thematic domains. A socio-technical lens guided interpretation, situating AI systems within broader institutional, regulatory, and socio-economic contexts rather than treating them as isolated technological artifacts.

Findings were ultimately organized into three primary analytical domains:

– Algorithmic Bias and Fairness
– Health Equity and Structural Disparities
– Digital Access and Governance Challenges

This framework enabled the identification of cross-cutting structural themes that transcend isolated technological performance metrics. By emphasizing interconnections between data practices, institutional capacity, and regulatory oversight, the synthesis provides a holistic understanding of how AI integration in early oncology screening may shape — and be shaped by — systemic inequities.

3. Results

3.1 Structural Overview of the Evidence

Across the ten core studies [1–10], ethical concerns surrounding AI in early oncology screening are framed not as isolated technical imperfections but as systemic risks embedded within healthcare infrastructures. Rather than conceptualizing bias as a correctable coding error or dataset limitation, the reviewed literature consistently situates AI systems within broader socio-technical ecosystems that include institutional funding models, reimbursement incentives, regulatory regimes, historical screening disparities, and digital access inequalities.

A recurring theme across publications is that AI systems are neither neutral nor context-independent technologies. Instead, they are developed, validated, and deployed within health systems that are already marked by uneven access to diagnostic services and differential participation in screening programs. Several authors emphasize that AI systems are trained on historically generated clinical datasets that reflect pre-existing structural asymmetries in access to screening, diagnostic follow-up, and specialty care [1,6]. These asymmetries may include underrepresentation of rural populations, minority communities, or patients treated in safety-net institutions.

As a result, AI models may inherit and scale patterns of underrepresentation, delayed diagnosis, or incomplete follow-up affecting marginalized populations. What appears as algorithmic optimization in controlled validation settings may therefore translate into the amplification of existing inequities when implemented at scale. The literature converges around a central insight: AI does not enter a neutral environment. Its real-world effects are mediated by institutional capacity, regulatory oversight, and the social determinants shaping patient pathways.

In this sense, AI in oncology screening is conceptualized not merely as a diagnostic enhancement but as a structural intervention whose impact depends on the conditions of its integration.

3.2 Algorithmic Bias as a Systemic Risk

Algorithmic bias is consistently identified as a foundational ethical concern across the reviewed studies [1,3,6]. Importantly, bias is conceptualized not solely as statistical imbalance or dataset insufficiency, but as the reflection of structural inequities embedded in training data, feature engineering, and validation practices. The literature emphasizes that algorithmic systems may encode historical patterns of exclusion or differential care even in the absence of explicitly discriminatory intent.

Evidence from broader healthcare AI research demonstrates real-world harm from biased population-level algorithms. Notably, risk prediction tools have been shown to systematically underestimate health needs among Black patients due to reliance on cost-based proxy variables that reflect unequal access to care rather than true disease burden [12]. Although not oncology-specific, these findings establish a critical precedent for understanding how screening algorithms may reproduce disparities when proxy indicators stand in for underlying clinical risk.

Imaging-based analyses further document subgroup performance variability in AI systems trained on non-representative datasets. Underdiagnosis bias has been observed in underserved patient populations when deep learning models are validated primarily on data from high-resource academic centers [15]. Moreover, studies demonstrate that AI systems can infer protected characteristics such as race directly from medical images—even when race is not explicitly included as a variable—indicating latent encoding of sensitive demographic attributes [3,4]. This phenomenon complicates simplistic fairness strategies based solely on removing demographic inputs, as protected characteristics may remain algorithmically embedded.

Collectively, the literature underscores that high aggregate accuracy does not guarantee equitable performance across subgroups. The reviewed studies consistently advocate for demographic performance reporting, bias auditing, intersectional validation, and transparent documentation of model development processes as essential safeguards [3,15]. Fairness, in this framing, is not a secondary optimization target but a primary ethical requirement in population-level screening contexts.

3.3 Amplification of Existing Disparities

Multiple studies frame AI not merely as a diagnostic tool but as a structural intervention embedded within already unequal health systems [2,6,16]. Rather than automatically reducing disparities, AI technologies may interact with pre-existing institutional and socioeconomic inequalities in ways that reinforce them.

In high-income contexts, AI-enhanced screening technologies are most rapidly adopted by well-funded academic medical centers with advanced digital infrastructures, robust IT departments, and established research collaborations. This pattern generates what may be described as a resource concentration dynamic, whereby technological innovation disproportionately benefits populations already advantaged by geography, insurance status, digital literacy, and institutional proximity.

Srivastav et al. argue that integrating social determinants of health (SDOH) into AI frameworks may offer pathways toward mitigating disparities by contextualizing risk beyond purely biological indicators [16]. However, the authors also caution that such integration requires careful design to avoid reinforcing stigmatizing or deficit-based models. Dankwa-Mullan et al. explicitly question whether AI will bridge or widen the cancer equity gap, emphasizing that deployment conditions, reimbursement incentives, and institutional readiness ultimately determine distributive outcomes [2].

The reviewed studies collectively caution against technological determinism—the assumption that innovation inherently produces social benefit. Without deliberate redistribution mechanisms—such as inclusive validation cohorts, equity-adjusted reimbursement policies, and targeted infrastructural investment—AI deployment may widen outcome gaps in early cancer detection. Screening technologies that enhance detection in already well-served populations may inadvertently deepen disparities in settings where access barriers remain unaddressed.

3.4 Digital Implementation Gap and Governance Constraints

Beyond algorithmic design, the literature highlights a persistent digital implementation gap as a decisive determinant of equitable AI integration. AI-based screening systems require high-resolution imaging technologies, interoperable electronic health records, secure data storage, computational capacity, and trained personnel capable of interpreting and auditing algorithmic outputs.

In low- and middle-income countries (LMICs), governance frameworks, regulatory oversight capacity, and digital infrastructure may be insufficient to support safe and equitable implementation [2,18]. Even when AI models are technically validated in high-income contexts, their transferability to resource-limited environments remains uncertain. Differences in disease prevalence, imaging protocols, equipment quality, and data completeness may affect model generalizability.

Zhang et al. emphasize the need for governance models explicitly tailored to LMIC settings to prevent technological dependence, inequitable knowledge transfer, and asymmetrical data extraction [18]. Without context-sensitive validation and local stakeholder engagement, AI deployment risks replicating patterns of global health inequity in digital form.

At the regulatory level, concerns about transparency, auditability, and liability further complicate equitable implementation. Ethical scholarship warns that algorithmic opacity—particularly in proprietary systems—may limit external scrutiny and obscure subgroup performance disparities [7,8]. In population-level screening programs, such governance gaps carry amplified ethical consequences, as systematic underperformance may affect entire demographic groups simultaneously rather than isolated individuals.

Collectively, the evidence indicates that digital infrastructure and governance capacity function as structural determinants of AI's equity impact in oncology screening. Technological capability alone is insufficient; equitable outcomes depend on regulatory preparedness, institutional accountability, and inclusive implementation strategies.

4. Discussion

4.1 AI in Oncology as a Socio-Technical Power Structure

The findings of this review support a decisive shift from viewing AI in early oncology screening as a purely diagnostic enhancement to understanding it as a socio-technical power structure embedded within existing health systems. Rather than functioning as a neutral computational tool, AI operates within layered institutional, economic, and regulatory environments that shape its development, validation, and implementation.

AI does not operate in isolation; it is trained on historically generated clinical data, validated within specific institutional contexts, and deployed according to reimbursement structures, procurement policies, and regulatory logics [2,6]. These contextual factors are not peripheral—they fundamentally influence whose data are included, which performance thresholds are prioritized, and where implementation occurs first. From this perspective, AI systems inherit the structural asymmetries of the environments in which they are developed and implemented. Historical inequities in screening participation, diagnostic follow-up, and access to specialty care may become embedded in training datasets and subsequently reproduced at scale.

Rather than functioning as neutral optimization tools, AI models may encode patterns of historical underdiagnosis, uneven screening uptake, and institutional resource stratification. When deployed in population-level programs, these encoded patterns can be amplified rather than corrected. This reinforces the argument that innovation without structural reform risks reproducing inequity at algorithmic scale. AI therefore emerges not only as a technical intervention but as a redistributive force whose impact depends on governance conditions, infrastructural readiness, and equity-oriented policy design.

Understanding AI as a socio-technical system shifts the evaluative question from "Does the model improve accuracy?" to "How does the model interact with existing structural inequalities?" This reframing is central to responsible implementation in early oncology screening.

4.2 The Illusion of Algorithmic Neutrality

A central tension identified across the reviewed literature is the persistence of what may be termed the "neutrality assumption" — the belief that improved technical accuracy automatically translates into equitable clinical outcomes. This assumption is often implicit in performance-driven validation studies that emphasize aggregate metrics such as sensitivity, specificity, or AUC without disaggregating results across demographic subgroups.

However, aggregate performance metrics obscure subgroup variability [3,4,15]. Models demonstrating high overall sensitivity may still underperform for specific demographic groups, particularly when validation cohorts are not demographically representative. In population-level screening, even modest reductions in sensitivity for marginalized groups can translate into disproportionately missed diagnoses, delayed treatment, and compounding disparities.

Moreover, proprietary model architectures and limited transparency in commercial AI systems restrict independent scrutiny. In population-level screening programs, such opacity raises ethical concerns, particularly when algorithmic recommendations influence diagnostic pathways for asymptomatic individuals who may be unaware of the algorithmic processes shaping their care [7,10]. Without accessible documentation of training data composition, feature selection strategies, and subgroup performance metrics, disparities may remain statistically invisible.

The ethical challenge, therefore, lies not only in correcting bias when detected, but in rejecting the assumption that technological optimization inherently aligns with distributive justice. Fairness must be explicitly defined, operationalized, and monitored, rather than inferred from overall performance improvements.

4.3 Data Inequality and Global Validation Gaps

Another structural vulnerability identified in this review lies in data concentration. The majority of AI oncology tools are developed and validated in high-income academic medical centers with robust digital infrastructures and well-curated datasets. While these environments enable technical innovation, they also produce validation asymmetry: models optimized for well-resourced settings are frequently generalized to contexts with different epidemiological profiles, healthcare access patterns, and infrastructural constraints.

In LMIC contexts, such generalization may result in reduced model generalizability and widening global screening disparities [2,18]. Differences in disease prevalence, imaging protocols, equipment quality, and follow-up pathways can affect model calibration and predictive performance. The absence of globally representative datasets reinforces what may be described as epistemic inequity—where certain populations are systematically underrepresented in the data ecosystems that shape medical innovation.

This epistemic imbalance has practical implications. If AI systems are trained predominantly on data from populations with stable access to healthcare, they may fail to account for delayed presentation patterns, comorbidity profiles, or socioeconomic barriers present in other settings. Addressing this challenge requires not only technical fairness mechanisms but also transnational data governance frameworks, equitable research collaborations, and inclusive dataset construction strategies that avoid extractive data practices.

Without deliberate efforts to diversify training data and validation environments, AI risks becoming a tool that codifies global inequities rather than mitigating them.

4.4 Regulatory Preparedness and Institutional Accountability

The review highlights a consistent regulatory lag relative to the rapid pace of technological innovation. While clinical validation standards exist for device performance, fewer standardized protocols explicitly address equity validation prior to large-scale deployment [7,8,10]. Current regulatory frameworks often prioritize safety and efficacy, but they may insufficiently operationalize distributive fairness or subgroup performance auditing.

Screening differs from individualized diagnostics in its population-level implications. If an AI system systematically underdetects lesions in a specific demographic group, the resulting harm is collective rather than isolated. This magnifies the ethical stakes of equity oversight.

Current regulatory structures often lack mandatory bias impact assessments or standardized requirements for demographic disaggregation of performance metrics [8,10]. The absence of such safeguards creates a governance gap in which inequitable outcomes may only become visible after widespread implementation. This gap suggests the need for:

– mandatory pre-deployment bias impact assessments,
– post-deployment equity monitoring and real-world performance audits,
– publicly accessible model documentation and transparency standards,
– interdisciplinary oversight bodies integrating clinical, ethical, and technical expertise.

Without these mechanisms, AI risks becoming an unregulated amplifier of institutional advantage, benefiting systems with greater digital capacity while marginalizing those without equivalent oversight resources.

4.5 Infrastructure as a Precondition of Equity

Beyond algorithmic design and governance mechanisms, this review underscores digital infrastructure as a prerequisite for equitable AI integration. AI-enabled screening depends on high-resolution imaging systems, interoperable electronic health records, secure data storage, computational capacity, and trained personnel capable of interpreting outputs and conducting audits.

These infrastructural prerequisites remain unevenly distributed both within and across countries [2,18]. Rural institutions, underfunded public hospitals, and healthcare systems in LMICs may lack the foundational conditions necessary for safe AI deployment. Consequently, AI may inadvertently privilege digitally mature health systems while excluding under-resourced institutions.

Innovation, therefore, cannot be disentangled from infrastructural investment. Without targeted support for digital capacity-building and workforce training, AI implementation may reinforce existing gradients of technological privilege. In this sense, digital readiness becomes a structural determinant of early cancer detection outcomes.

4.6 Reframing Responsible Innovation

Taken together, the findings indicate that responsible AI integration in oncology requires reframing prevailing innovation metrics. The dominant paradigm of performance-centered validation prioritizes incremental gains in diagnostic precision, often measured in controlled environments. However, such gains may not translate into equitable population-level benefit.

Rather than evaluating AI solely on improvements in diagnostic accuracy, ethical deployment should be assessed according to its capacity to reduce disparities across demographic groups and healthcare settings [2,8]. This implies a transition from performance-centered validation to equity-centered governance, where algorithmic systems are judged not only by how accurately they detect cancer, but by whom they serve effectively.

Responsible innovation in early oncology screening must therefore integrate fairness auditing, inclusive validation cohorts, infrastructural investment, and longitudinal monitoring of real-world outcomes. Only through this broader evaluative lens can AI function as a tool for narrowing rather than widening disparities.

4.7 Limitations

This review is limited by its focus on PubMed-indexed review and policy literature published between 2018 and 2026. The analytical corpus emphasizes conceptual and governance-oriented analyses rather than empirical subgroup performance trials, which may limit the ability to quantify real-world disparity effects.

Additionally, AI technologies and regulatory landscapes evolve rapidly. Emerging fairness frameworks, transparency mandates, and dataset diversification initiatives may alter implementation dynamics over time. Future research should include longitudinal evaluations of equity outcomes following real-world deployment of AI-based screening tools, particularly in diverse geographic and socioeconomic contexts.

5. Conclusions

The rapid integration of artificial intelligence into early oncology screening represents one of the most consequential technological shifts in contemporary medicine. AI-driven imaging analysis, predictive modeling, and risk stratification tools hold substantial promise for improving early cancer detection, reducing diagnostic variability, and optimizing population-level screening strategies [9,16]. In controlled validation environments, these systems demonstrate measurable improvements in sensitivity and efficiency, reinforcing expectations that AI may enhance clinical workflows and expand diagnostic capacity.

However, this review of the selected studies demonstrates that technological acceleration is unfolding within health systems already marked by structural inequities [2,6]. AI does not emerge in a vacuum; it is introduced into institutional contexts characterized by uneven access to screening, differential digital infrastructure, and historically patterned disparities in healthcare delivery. As such, the distributive consequences of AI integration depend not solely on algorithmic accuracy but on the social and regulatory environments governing its deployment.

The findings indicate that AI is not a neutral instrument of progress. Its impact is mediated by dataset representativeness, institutional resources, digital maturity, workforce capacity, and regulatory preparedness. Without equity-sensitive oversight, AI systems trained on historically skewed datasets may reproduce patterns of underdiagnosis or limited access among marginalized populations. In the absence of deliberate governance mechanisms, AI deployment may reinforce existing disparities in access to early detection, particularly among socioeconomically disadvantaged groups and in low- and middle-income countries (LMICs) [2,18]. Importantly, aggregate improvements in diagnostic accuracy do not automatically translate into equitable health outcomes; population-level fairness requires subgroup-sensitive validation and structural safeguards.

This review therefore underscores the need to reframe innovation in oncology screening through an equity-centered lens. Ensuring that AI functions as a tool for narrowing rather than widening disparities requires a paradigm shift from performance-centered validation to equity-centered implementation [2,8]. Such a shift entails mandatory demographic performance reporting, intersectional bias auditing, inclusive and globally representative dataset construction, infrastructure investment in underserved regions, and transparent regulatory oversight mechanisms capable of monitoring real-world equity outcomes over time.

Moreover, responsible AI integration must be understood as a long-term governance challenge rather than a one-time validation milestone. Sustainable deployment requires interdisciplinary collaboration among clinicians, data scientists, ethicists, policymakers, and public health stakeholders. Equity considerations must be embedded at each stage of the AI lifecycle—from data acquisition and model design to post-deployment monitoring and regulatory review.

Ultimately, the promise of AI in early oncology screening lies not only in its capacity to detect malignancy with greater precision, but in its potential to contribute to more just and inclusive healthcare systems. Whether AI becomes a tool of disparity reduction or disparity amplification will depend on the intentional alignment of technological innovation with principles of transparency, accountability, and global health equity. Only by embedding algorithmic systems within accountable, socially responsive frameworks can the transformative potential of AI in early cancer detection be realized in a manner consistent with distributive justice and public health responsibility.

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