

Equitable and Sustainable Healthcare AI: Tackling Data Bias with Managerial Governance and SDG Alignment

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Abstract

Artificial intelligence (AI) is being applied in healthcare to make care more effective and efficient and to improve diagnosis, patient care, and operations. However, research has shown how AI can perpetuate and even magnify historical and structural biases present in data, creating new or further inequitable or unfair outcomes. Data bias and algorithmic fairness are, therefore, an ethical, managerial, operational, and sustainability issue. This literature review paper distills and synthesizes 27 studies, takes a managerial perspective on data bias in AI in healthcare, and integrates the technical, organizational, and governance dimensions. The paper develops a bias governance framework that connects healthcare AI use with the SDGs 3, 9, and 10, and that can be used by leaders, policymakers and managers in digital healthcare to take action.

Keywords: Healthcare AI, Data Bias, Algorithmic Fairness, Management, SDGs, Governance, Responsible AI

INTRODUCTION

Artificial intelligence (AI) has become an integral part of contemporary healthcare, shaping clinical judgments, organizational workflows, and strategic decision-making with the promise of greater efficiency and improved patient outcomes. Yet, evidence from recent research shows that these systems often inherit and intensify long-standing inequities embedded in healthcare data, leading to uneven and sometimes harmful consequences for already disadvantaged populations. Bias arising from skewed datasets, historically rooted clinical practices, and fragmented data infrastructures challenges the assumption that AI-driven decisions are objective or neutral. As a result, data bias and algorithmic fairness now represent pressing concerns that extend beyond technical design to encompass managerial responsibility, governance arrangements, and the long-term sustainability of digital health initiatives.

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Despite growing scholarly attention to bias detection and mitigation techniques, the organizational and leadership dimensions of managing biased AI systems remain insufficiently explored. Addressing this gap, this study synthesizes insights from 27 peer-reviewed studies to examine data bias in healthcare AI from a managerial perspective. It advances a bias governance framework that connects responsible AI use with the United Nations Sustainable Development Goals-particularly SDG 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 10 (Reduced Inequalities)-offering practical direction for leaders and policymakers seeking to build fair, accountable, and sustainable healthcare systems.

Problem Statement

AI in healthcare is growing fast. However, there is growing evidence that it can also inadvertently perpetuate historical and structural inequities, as AI models can be no better than the data they are trained on. As a result, healthcare organizations experience negative repercussions of biased AI at not only the technical but also the ethical, managerial, operational, and sustainability levels. A 2022 study of a predictive model frequently used to estimate the risk of developing sepsis, for example, found that the algorithm systematically underprioritized Black patients because historical claims cost data was used as a proxy for severity, but underrepresented the real health needs of Black patients ^[13,17]. Hospitals that implemented the model, as a result, suffered at the operational, ethical, and managerial levels in the form of delayed care, adverse patient outcomes, and managerial overhead, respectively ^[13,17].

Significance to Healthcare Management

AI bias is a managerial problem with a set of intricate technical, ethical, regulatory, and sustainability dimensions that cut across the strategic, operational, and sustainability risk and control functions of management ^[1-27]:

- 1 **Algorithmic Fairness:** The quality and representativeness of data that forms the basis of AI models have strategic, operational, and sustainability implications for healthcare organizations ^[1-27].
- 2 **Health Equity:** Bias in AI can pose health equity risks of perpetuating or amplifying existing healthcare inequities. This can have both operational and reputational implications for healthcare organizations and the sector as a whole ^[10,13,17].
- 3 **ESG and SDG Accountability:** Healthcare organizations face increasing external accountability to ESG and SDG targets. The choice of AI models and decision logic, as a result, can have both external sustainability implications and internal operational risk and should be considered by managers in decision-making ^[13,24-27].

- 4 **Regulation:** The introduction of AI regulations, guidelines, and recommendations (e.g., EU AI Act, HIPAA, ISO/IEC AIE PS, etc.) also poses risks to healthcare organizations if not integrated in strategic and operational decisions by leadership, impacted staff, and operations ^[25,26].

AI bias thus poses a critical risk, operational, and sustainability concern for healthcare organizations that must be addressed and governed by healthcare leaders.

Sustainability Rationale

Ensuring alignment with ESG and SDG goals when deploying AI while mitigating bias and ensuring fairness furthers the sustainability goal of more equitable and inclusive healthcare. SDGs 3, 9, and 10 connect directly with this effort by mandating good health and well-being, responsible innovation and infrastructure, and reduced inequality and inclusivity, respectively ^[13,24–27]. Integrating this goal with AI governance in healthcare directly enables managers to advance healthcare delivery sustainability objectives through their organizational choices.

OBJECTIVES OF THE STUDY

This literature review aims to:

- 1 Review and Synthesize evidence on data bias in AI in healthcare applications, including diagnostic imaging, predictive analytics, and clinical decision support, to take a managerial perspective on organizational and algorithmic risk and governance gaps.
- 2 Examine management and organizational levers that create or amplify bias, such as data management practices, business workflows, and leadership decisions.
- 3 Align actions for bias mitigation with SDGs (3, 9, 10) and provide concrete linkage of the steps to sustainability, showing how responsible and equitable AI supports sustainability in healthcare.
- 4 Propose an actionable bias governance framework that integrates ethical, operational, and strategic-level considerations to inform healthcare leadership, policymakers, and practitioners in digital healthcare operations ^[1–27].

Contributions of the Study

This paper makes contributions to academia and practice in:

- 1 Reviewing and bridging AI bias in healthcare literature with managerial, sustainability, and ESG literature.
- 2 Proposing a concrete bias governance framework for healthcare organizations with detailed action steps, processes, and SDG alignment.

- 3 Providing actionable managerial guidance for healthcare leaders, practitioners, and policymakers on a critical technical, ethical, and sustainability topic.
- 4 Highlighting research and practice gaps to guide future scholarly and practical attention to bias and AI in healthcare from a managerial and ESG/SDG perspective ^[1-27].

Case Example

AI in Skin Cancer Diagnosis has been shown to have reduced accuracy for people with darker skin tones than the training data ^[23]. This directly impacts operational efficiency, adverse patient outcomes, patient trust, and manager liability at healthcare organizations, highlighting the practical business, ethical, and sustainability impacts of this challenge.

EXPANDED LITERATURE REVIEW

Types of Bias in Healthcare AI

- 1 **Historical and Structural Bias** : AI models in healthcare are at risk of historical inequities that are encoded in the data and therefore will repeat or amplify this unfairness in the model outputs ^[1,13]. This is common in structural inequities, where specific populations are systematically advantaged or disadvantaged in healthcare utilization patterns based on historical, regulatory, or provider biases -urban hospitals having more investment and therefore more patients than rural clinics, insurance networks favoring specific providers and treatments, certain procedures being less accessible in certain regions, etc.

Case Example: AI-based risk-scoring models used in U.S. hospitals were found to recommend fewer healthcare resources to Black patients because the algorithm used historical cost of care as a proxy for health needs ^[13,17].

Managerial Implication : Healthcare managers and leaders must review the data and question its representativeness, integrating a lens of bias and fairness into organizational decisions like staffing, policy, and operations ^[2,15,20].

- 2 **Representation Bias** : Datasets for AI in healthcare may be incomplete in the sense that certain demographic or clinical subgroups are underrepresented. This results in AI models trained on these data being less accurate or fair for the clinical decision support of those underrepresented populations ^[9,14,23].

Case Example : Dermatology imaging AI tools for skin lesion detection and classification have shown reduced accuracy and increased misclassification for patients with dark skin lesions because the datasets included a very small number of darker-skinned patients ^[23].

Managerial Implication : Healthcare managers should ensure that data collected is inclusive of all relevant patient subgroups and monitor model performance for each subgroup, as poor algorithmic performance can have adverse effects on patient safety, operational liability, and patient trust ^[7,12,24–27].

- 3 **Measurement and Proxy Bias :** Bias also occurs when a model uses an indirect variable (proxy) as a substitute for a desired target variable. A common example in healthcare AI is using healthcare cost as a proxy for illness or disease severity. Cost is convenient to calculate, but it poorly represents the actual clinical needs of patients who may have different healthcare access and utilization patterns due to historical, provider, or other biases (e.g. Black Americans in the U.S.) ^[13].

Case Example : AI models to predict chronic disease risk in a healthcare system have been found to deprioritize low-income or minority patients when deployed in the real world, despite higher levels of clinical risk for these groups ^[13,17].

Managerial Implication : Bias mitigation requires identifying proxy variables and thinking critically about how well they represent health needs or risk across patient groups ^[3,9,13]. Bias, therefore, has direct managerial implications for clinical outcomes, patient trust, and operations.

- 4 **Institutional and Organizational Bias :** AI bias can also be introduced or exacerbated by institutional and organizational data management, governance, and operational choices. Selective documentation of clinical variables or coding for administrative claims, incomplete or inconsistent data entry, and other workflow decisions result in an incomplete or biased underlying dataset that will train a model to be biased in its decisions and outputs ^[2,18].

Case Example : A study of electronic record keeping practices and AI model performance in a network of hospitals showed a 12–18% higher misclassification rate (poorer performance) in institutions that had inconsistent or missing documentation practices ^[18,20].

Managerial Implication : Hospital administrators and healthcare leaders must consider internal documentation and data collection standards as critical to algorithmic outputs and patient outcomes. Institutional bias in data and models must be audited and monitored as it has direct patient safety and organizational risk implications for healthcare institutions ^[7,12,24–27].

Managerial and Ethical Perspectives

AI bias is fundamentally an organizational and ethical issue that must be considered in strategic, ethical, and operational oversight and decision-making ^[7,12]. The consequences of deploying AI with biased models and data are as follows:

- 1 **Ethical and Patient Safety Oversight** : Health equity, fairness, transparency, and accountability for patient safety are a priority ^[7,12].
- 2 **Operational and Business Risks** : The organization has an appreciation that bias can have direct liability and business implications for the organization ^[16,21].
- 3 **Strategic Embedding** : A consideration of bias and AI alignment with strategic, ESG, and SDG goals and embedding of mitigation actions in operations and culture ^[13,24–27].

Case Example

One hospital that encountered issues with AI equity established an AI Ethics Committee that included clinicians, IT staff, and patient representatives to vet all AI models prior to use. This led to demonstrable improvements in fairness metrics and a reduction in bias-related incidents ^[12,24].

EVIDENCE ACROSS HEALTHCARE APPLICATIONS

- 1 **Clinical Decision Support Systems (CDSS)** : AI models that support clinicians' treatment decisions, also known as CDSS, are prone to bias and inequities in performance due to similar data and bias challenges. For example, a model that uses the frequency of lab tests to determine health risk may interpret patients who are tested less frequently as being lower risk. But this may not represent the true underlying risk for high-risk minority patients who have lower historical utilization of care ^[19].
- 2 **Diagnostic Imaging Algorithms** : AI used for image classification in medicine, such as dermatology, radiology, or ophthalmology, is often less accurate for populations who were underrepresented in training images. For example, skin lesion classifiers and dermatology AI perform worse in darker-skinned patients when trained on lighter-skinned patients' images ^[23].
- 3 **Population Health Management Tools** : Predictive models used in population health management to allocate healthcare resources, identify chronic disease management, or stratify risk for preventive care often use historical claims cost or healthcare utilization data, which encode historical system inequities when applied to certain clinical or demographic subgroups (urban versus rural hospitals, minority communities, uninsured, etc.) ^[13,17].

Managerial Implications Across Applications

AI bias is a managerial concern for healthcare leaders, requiring cross-functional governance, continuous auditing of model performance, and operational strategy alignment to ensure equitable and fair algorithmic outputs ^[7,12,24–27].

Case Table

Table 1. Illustrative Cases of AI Bias in Healthcare and Managerial Actions

Application	Type of Bias	Outcome	Managerial Action
Sepsis Risk Prediction	Proxy Bias	Black patients underprioritized	Revise proxy variables, governance review [13,17]
Dermatology Imaging	Representation Bias	Misclassification of dark skin lesions	Inclusive dataset, performance monitoring [23]
Chronic Disease Risk	Structural Bias	Low-income patients deprioritized	Cross-functional oversight, data augmentation [13]
Multi-Hospital Records	Institutional Bias	Misclassification due to inconsistent EHRs	Standardize records, internal audits [18,20]

Summary of Key Research Findings and Managerial Insights

Our literature review about bias in AI for healthcare has corroborated several key points from the existing literature that highlight that bias is indeed multidimensional and caused by numerous factors, including historical, representational, proxy and organizational causes. Managerial and leadership responses to these challenges are a necessary enabler of risk mitigation and responsible, equitable, and sustainable AI within healthcare organizations [1–27].

MANAGERIAL IMPLICATIONS

Managerial Implications of Strategic Risks Associated with Biased AI

Strategically, the use of biased AI models in healthcare delivery and management without AI risk governance mechanisms can expose organizations to the following risks:

- **Noncompliance and reporting issues:** As AI governance frameworks and regulations are still being developed (e.g., EU AI Act guidelines [25], ISO/IEC standards [26], U.S. HIPAA), AI systems are expected to be fair, transparent, and accountable, as well as not target, stereotype, or reinforce biases against protected and vulnerable populations. The implications of noncompliance with reporting, auditing, and mitigating bias are financial penalties, operational restrictions, and regulatory audits [2,15].

Case Example : A hospital's AI triage predictive model had been deprioritizing minority patients for ICU admission. Following public outcry and a patient lawsuit, the hospital board had to address its failure to proactively govern AI transparency and accountability to maintain the public trust [10,12,24].

Managerial Implications of Operational Risks

AI models with high false negative/false positive rates can introduce substantial operational inefficiencies, such as:

- Redundant testing, investigations, and delays in patient care and interventions
- Inefficient resource utilization, allocation of staff, or unnecessary overstaffing
- Disruption of workflows or inefficient scheduling of procedures or treatments [6,17].

Case Example : Predictive risk stratification models for the management of chronic diseases misclassified rural patients at a rate 15% higher than urban/suburban patients as a result of proxy bias in risk variables included in the model. Inefficiencies in operations resulted in higher hospitalization and operational costs which managers had to offset by modifying their data collection standards and model auditing procedures [13,17].

Managerial Insight : To mitigate potential bias-associated operational risks and inefficiencies, AI managers should implement risk auditing systems that flag the introduction of biases which can result in workflow disruptions. These may include a real-time operational dashboard, cross-department algorithm auditing, and feedback loops to detect and immediately address operational risks.

Managerial Implications of Reputational and Compliance Risks

Patient trust and satisfaction may be jeopardized by errors introduced by AI. Negative public experiences can cause low adoption, and even a single perceived instance of inequity can create mistrust towards the provider or health system. Bias in AI can lead to:

- Loss of credibility and reputation with patients, communities, other stakeholders, or investors
- Decrease in patient referrals and hospital visits.
- Challenges to business continuity and resourcing [10,12,24].

Case Example : A diagnostic platform driven by AI misdiagnosed multiple minority patients in a large teaching hospital, triggering media coverage and regulatory investigation. The hospital's management realized the need for governance, reporting, and communication plans for effective transparency on AI decisions [7,12,24–27].

Managerial Implications of Strategic Sustainability Risks

Bias in AI runs counter to ESG and SDG expectations. Increased stakeholder accountability has been placed on organizations to drive ethical and inclusive AI systems ^[13,24–27].

Misalignment of bias in AI with SDGs 3, 9, and 10 can affect collaboration and reporting on sustainability KPIs and affect access to funding or sustainability partnerships ^[13,24–27].

Practical Implication : Hospital managers should link organizational-level bias governance on AI with ESG targets and KPIs. This can include tracking algorithmic fairness, operational inefficiencies, and alignment to SDGs (3, 9, and 10) as part of AI decision-making.

Summary Table of Managerial Implications

Table 2 : Managerial Risks and Recommended Actions

Risk Type	Description	Managerial Action
Strategic	Regulatory non-compliance, reputational loss	Implement AI ethics committees, transparent reporting ^[10,12]
Operational	Resource misallocation, delayed care	Deploy dashboards, audits, and feedback loops ^[6,17]
Compliance	Legal exposure, stakeholder mistrust	Adhere to ISO/IEC standards, SDG alignment ^[24–27]
Sustainability	Misaligned ESG & SDG objectives	Link AI governance to SDG reporting ^[13,24–27]

GOVERNANCE FRAMEWORK FOR BIAS MITIGATION

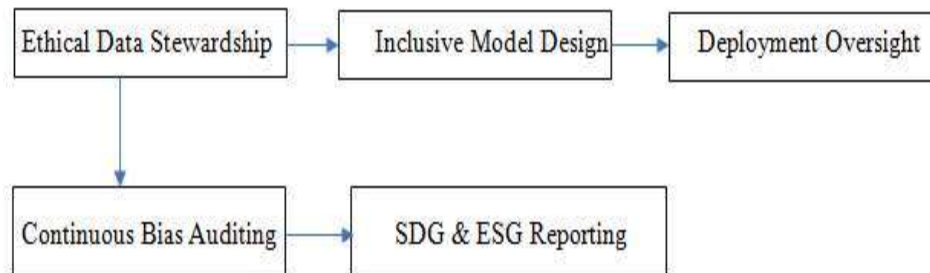
Principles of Bias Governance

The following four key principles can underpin bias governance:

1. **Ethical Stewardship** : AI use and outputs should be fair and aligned with patient rights and equity ^[2,18,24].
2. **Inclusivity** : This includes diverse populations in data sources and stakeholder committees ^[7,12].
3. **Accountability** : Define and assign roles and responsibilities for leaders, data scientists, and clinicians ^[24].

4. **Continuous Monitoring** : Require periodic auditing and feedback mechanisms to identify new biases ^[7,12,24–27].

Lifecycle-Based Governance Model



Detailed Components

- 1 **Ethical Data Stewardship** : Include representativeness, validation, and inclusiveness of datasets ^[2,18,24].
- 2 **Inclusive Model Design** : This involves demographic-aware and proxy-checked algorithms for fairness ^[3,9,13].
- 3 **Deployment Oversight** : Multidisciplinary committees to oversee AI outputs and reporting ^[15,20].
- 4 **Continuous Bias Auditing** : This requires internal/external monitoring and KPI reporting ^[7,12].
- 5 **SDG & ESG Reporting** : Transparent documentation and KPI reporting linked to SDG 3, 9, 10 and organizational targets ^[13,24–27].

Case Example : A large metropolitan hospital developed and implemented the lifecycle model, creating an AI Governance Committee. It included cross-functional leaders (clinical, IT, compliance) and subcommittees to support key activities, including ethical oversight, monitoring, and reporting. Post-implementation audits of the high-risk prediction algorithms deployed found a 30% reduction in misclassification of minority patients ^[12,24].

Integration of Governance with Organizational Strategy

Bias governance should align with organizational strategy as follows:

- 1 Include strategic objectives on fair, responsible, and sustainable AI (such as SDG alignment).

- 2 The performance KPIs on algorithms and machine learning models should be reviewed regularly as part of oversight.
- 3 AI outputs should be linked to internal sustainability reporting to align with investor expectations ^[13,24–27].

SDG ALIGNMENT

Mapping Bias Mitigation to SDGs

Table 3 : SDG Alignment with Healthcare AI Bias Mitigation

SDG	Focus Area	Application to Healthcare AI
SDG 3 – Good Health & Well-being	Equitable patient outcomes	Inclusive datasets, unbiased algorithms ensure fair treatment ^[13,24]
SDG 9 – Industry, Innovation & Infrastructure	Responsible innovation	Lifecycle-based AI governance frameworks ^[24–26]
SDG 10 – Reduced Inequalities	Minimized disparities	Targeted interventions, representative training data ^[13,24,27]

Managerial Implications of SDG Alignment

- 1 AI aligned with the SDGs enhances organizational credibility with funders, investors, and talent ^[13,24–27].
- 2 Managers can incorporate SDG KPIs into AI operational dashboards to track fairness and progress in real-time.
- 3 Sustainable and responsible AI practices improve patient trust, reduce long-term risk, and support ethical cultures ^[24–27].

Case Example : A hospital system’s leadership connected AI KPIs to SDG 3 and 10, reporting 25% improvements in access to care for minority patients in their high-risk groups over a 12-month period. This demonstrated an improvement in SDG-aligned ESG impact reporting ^[24–27].

SDG-Centric Bias Governance Model



Figure 2: Textual Representation - SDG Alignment

Practical Implication : Managers can use bias mitigation as a strategic lever to improve care equity and operational efficiency while simultaneously meeting SDG commitments ^[13,24–27].

PRACTICAL MANAGERIAL RECOMMENDATIONS

- 1 Establish AI ethics committees with cross-disciplinary perspectives ^[7,12,24]
- 2 Incorporate bias evaluation metrics into regular operational dashboards ^[16,21]
- 3 Provide training and workshops on responsible AI deployment practices ^[11,24]
- 4 Align, monitor, and report AI deployment activities to SDGs and sustainability reports ^[13,24–27]
- 5 Plan external audits, assess and engage key stakeholders ^[20,25]

CONCLUSION

AI in healthcare can advance diagnosis, prediction, patient management, and efficiency gains. In practice, however, as we have seen in this review of studies, data bias continues to be a major challenge, and historical, structural, representational, proxy, and institutional biases have been observed across AI applications and use cases in healthcare ^[1,13,17,23].

From the perspective of managers and healthcare organizations, bias presents strategic, operational, compliance, and sustainability risks, potentially resulting in regulatory actions, reputational loss, and resource waste if left unchecked ^[2,15,20]. Ethical frameworks and bias governance practices will be key to tailor AI to the organization's mission, delivering equitable care, and supporting SDG 3 (Good Health), SDG 9 (Innovation & Infrastructure), and SDG 10 (Reduced Inequalities) ^[13,24–27].

This study has proposed a governance framework to manage bias throughout the data-AI lifecycle: ethical data stewardship, inclusive model design, deployment

oversight, continuous auditing, and sustainability reporting linked to the SDGs. Bias mitigation efforts linked to corporate strategy, key performance KPIs, and sustainability goals can also contribute to building patient trust, operational resilience, and long-term success for healthcare organizations [7,12,24–27].

FUTURE RESEARCH

While this study has covered substantial evidence on the topic, several critical and unanswered research questions exist, that are left for future research efforts:

The Cost of Bias Quantification

Bias in healthcare AI has an operational and financial cost to healthcare organizations, patients, and healthcare systems that is not well understood or quantified in future research. Possible metrics may include misclassification rates, missed treatments, time-to-diagnosis, resource use, additional investigations, and legal/regulatory risks/liabilities [6,17].

Bias Governance in Low-Resource Settings

AI is implemented in low-resource hospitals or low-volume rural healthcare settings. These have specific contexts with poor availability of quality data, lack of skilled workforce, and resource and infrastructure constraints [21–23]. Future research can develop context-specific AI governance frameworks for these settings.

Standardization of SDG-Aligned Performance Indicators

AI managers can implement KPIs that standardize the tracking of algorithmic fairness, operational efficiencies, and sustainable practices. Future research can develop common KPIs linking minority patient outcomes, bias-mitigated AI processes, and SDGs 3, 9, 10 for hospitals to report improvements and impact [13,24–27].

Dynamic Bias Auditing Frameworks

AI models continuously learn new data, and this can lead to the risk of new biases. Future research can examine adaptive bias auditing frameworks, including real-time monitoring systems, feedback loops, and automated alerts to detect and address evolving risks [7,12,15].

Cross-Disciplinary Studies

Bias mitigation in AI requires managers, clinicians, data scientists, and researchers to collaborate. Future cross-disciplinary studies can generate evidence for governance models that include the perspectives and responsibilities of technical, clinical, and managerial stakeholders [7,12,24–27].

Case-Based Best Practices

Successful examples of AI bias mitigation in hospitals are not well reported in the literature. Future research can generate longitudinal and case-based studies to operationalize the proposed bias governance frameworks, SDG alignment, and managerial decision-making in practice.

Regulation and Policy Implications

AI governance is likely to evolve in the coming years (such as EU AI Act and ISO/IEC standards). Future research can examine the effectiveness of policy guidelines, implementation by organizations, and stakeholder accountability^[25,26].

Managerial Takeaway : Future research that is quantitative, qualitative, and cross-disciplinary will help organizations adopt equitable AI, improve patient outcomes, and create value for healthcare managers interested in responsible and sustainable AI^[1–27].

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