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Rewriting the Narrative of AI Bias: A Data Feminist Critique of Algorithmic Inequalities in Healthcare

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Abstract

AI-driven healthcare systems perpetuate gendered and racialised health inequalities, misdiagnosing marginalised populations due to historical exclusions in medical research and dataset construction. These disparities are further reinforced by androcentric medical epistemologies where white male bodies are treated as the universal norm. Additionally, the 'othering' of marginalised communities manifests in algorithmic exclusions or biases, where AI systems flag non-dominant populations as statistical anomalies rather than central subjects, reinforcing structural biases in healthcare access and treatment. This article critically examines the framing of AI bias within legal narratives, particularly through the EU AI Act, arguing that bias is not merely a technical flaw, but a structural consequence of exclusionary knowledge production. The study integrates data feminism as a counter-narrative to dominant AI governance frameworks, applying insights from Richard Sherwin's legal narrative theory, Kimberlé Crenshaw's intersectionality theory, Carol Smart's socio-legal critiques, and Ruha Benjamin's abolitionist AI perspectives. The analysis highlights how specific articles in the EU AI Act: risk-based classification (Article 6), bias audits (Article 10), and transparency requirements (Article 13), reinforce androcentric, racialised, and neoliberal exclusions, failing to mandate intersectional accountability or structural interventions. By challenging the formalist bias framing in AI regulation, the article advocates for equity-driven AI governance through data feminism, embedding data sovereignty, participatory oversight, and redistributive justice.

***Keywords**:* Algorithm bias; AI health; techno-governance; data feminism; bias framing; androcentricity; intersectionality.

1. Introduction: Framing AI Bias as a Structural Issue

Narratives exert a profound and multifaceted influence on the construction and interpretation of real-life experiences, constituting a fundamental aspect of human cognition and socio-cultural interaction. Spanning diverse mediums such as literature, folklore and personal discourse, narratives serve as both reflective mirrors and active agents in shaping individual and collective identities, perceptions and interpretations of reality. They provide a structured framework through which individuals contextualise their past, negotiate their present circumstances and project aspirations for the future. They possess a compelling capacity to engender empathy and facilitate intersubjective understanding by affording audiences the opportunity to vicariously engage with varied perspectives and lived realities. In essence, narratives emerge as pivotal conduits for the transmission of cultural values, ethical paradigms and collective memory, thereby contributing to the continual negotiation and evolution of societal norms and individual worldviews.

In health and medicine, narratives and storytelling serve as indispensable tools for conveying patient experiences, disseminating medical knowledge and fostering empathy among healthcare practitioners. However, the translation of narratives into medical discourse can inadvertently perpetuate historical inaccuracies and biases, thereby distorting clinical perceptions and exacerbating healthcare disparities. Historical narratives, shaped by prevailing sociocultural norms and power dynamics, may inadvertently marginalise certain patient populations or perpetuate stereotypes based on race, gender or socioeconomic status. Moreover, the selective emphasis on certain medical 'stories' over others may reinforce dominant biomedical paradigms while marginalising alternative healing traditions or patient perspectives. Consequently, this distortion has the potential to engender discriminatory practices within healthcare settings, further entrenching inequities in access to care and treatment outcomes. Thus, critical examination and contextualisation of these narratives are imperative to mitigate their potential for perpetuating historical inaccuracies and discriminatory practices within the field of medicine.

Meanwhile, the intersection of medical narratives with healthcare delivery and artificial intelligence (AI) introduces a complex interplay between subjective patient experiences, clinical data collection and algorithmic decision-making. While AI is increasingly being integrated into healthcare systems, promising efficiency, precision and improved patient outcomes, it is not neutral. It reflects the biases embedded in the data it processes, the algorithms that structure its decision-making, and the regulatory frameworks that govern its deployment. The inherent subjectivity and contextuality of medical narratives may be lost in translation, leading to an oversimplification or misrepresentation of patient experiences within datasets. Consequently, AI algorithms trained on such data risk perpetuating the biases and disparities[1] inherent in historical medical narratives, thereby compromising the equitable delivery of healthcare. The reliance on AI-driven decision support systems may exacerbate these issues by amplifying algorithmic biases and reinforcing existing healthcare inequalities.[2]

Despite these well-documented disparities, regulatory responses often frame bias as a technical flaw, a problem that can be corrected through mere improved data collection, algorithmic adjustments or transparency measures. This article challenges that assumption, arguing that AI bias is embedded within historical and legal narratives that have long marginalised intersectional identities in medicine and healthcare. Legal narratives do not merely describe reality; they construct it. As Sherwin argues, law operates through storytelling, shaping perceptions of justice, fairness and responsibility.[3] In the case of AI bias, the dominant legal narrative treats discrimination as an anomaly – something that can be corrected through technical adjustments rather than structural reform. This formalist legal narrative is evident in the European Union Artificial Intelligence Act ('the EU AI Act'),[4] which adopts a risk-based classification system to regulate AI applications. While this approach appears neutral, it implicitly prioritises concerns that align with dominant narratives of technological governance – which often overlook the gendered and intersectional dimensions of bias. By categorising AI systems based on their potential harms, the EU AI Act assumes that bias can be mitigated through technical safeguards rather than addressing the structural inequalities that shape algorithmic outcomes.

This article argues that data feminism, a theoretical feminist and intersectional approach, provides a counter-narrative to dominant AI governance frameworks. Data feminism, as articulated by D'Ignazio and Klein,[5] is a way of thinking about data, data systems and data science that encourages and validates a recognition that achieving true equality means needing to examine the root causes of inequalities that are faced particularly by intersectional groups.[6] By applying data feminism as a narrative framework, this article critiques the EU AI Act, demonstrating how its risk-based classification system, bias mitigation strategies and transparency requirements reinforce androcentric and technocratic assumptions in health and medicine. Hence, the inquiry of this article is threefold. First, how does the EU AI Act construct a regulatory narrative of AI bias, and what are its implications for health inequalities? Second, to what extent does the EU AI Act's risk-based classification system reinforce androcentric assumption in AI governance? Finally, how can data feminism serve as a counter-narrative that provides a more effective framework for addressing AI bias in health and medicine?

To achieve the answers to these questions, this article integrates three key approaches to demonstrate how AI bias is constructed within legal narratives or regulatory storytelling – and how this constructs visions of fairness, justice and inclusion (which often reinforces rather than dismantles systemic inequalities). The first approach utilises Sherwin's legal narrative theory to demonstrate how law shapes perceptions of bias and fairness.[7] The second approach relies on Kimberlé Crenshaw's intersectionality framework, which analyses how AI bias disproportionately affects marginalised groups;[8] finally, the third

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[1] Benjamin, Race After Technology.
[2] Noble, Algorithms of Oppression.
[3] Sherwin, "Law Frames."
[4] Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) (Text with EEA relevance).
[5] D'Ignazio and Klein, Data Feminism.
[6] D'Ignazio and Klein, "The Seven Principles."
[7] Sherwin, "Law Frames," 40.
[8] Crenshaw, "Demarginalizing the Intersection."

approach carefully reflects Carol Smart's socio-legal critique of androcentricity,[9] which is applied to show how gendered assumptions persist in AI governance. To this end, section 2 provides a background to AI bias and health inequalities, with section 3 examining androcentricity and intersectionality in AI regulation, exploring how gendered and racial biases persist in medical AI. Section 4 proposes the concept of data feminism as a counter-narrative and analyses the EU AI Act's bias-mitigation strategies, transparency requirements and risk-classification system to demonstrate how these reinforce androcentric assumptions. Section 5 concludes the article by advocating for a narrative transformation in AI regulation to ensure that AI systems actively work towards structural justice rather than merely mitigating bias.

2. Narratives of AI Bias and Health Inequalities

As indicated in section 1, this article challenges the framing of technologies as being neutral and objective. Despite the deployment of AI across healthcare systems, the reality is that it inherits and amplifies existing biases embedded in medical research, healthcare policies and systemic inequalities.[10] These obscured and hidden biases encapsulate contributions that have been cloaked in the fabric of the development of AI systems tailored for healthcare applications. With the incessant surge in the evolution of both health and medical AI paradigms, it becomes imperative to acknowledge the ramifications of these biases on diverse and intersectional demographic cohorts. There is now a need to accentuate the exigency for the adoption of intersectionality-conscious AI architectures aimed at curtailing the unintentional detriments engendered by AI biases.

Marginalised communities – including women, racial minorities, disabled individuals, and lower-income patients[11] – face disproportionately higher risks of misdiagnosis, inadequate treatment and exclusion from AI-driven healthcare innovations.[12] These inequalities are not accidental; they are a direct result of androcentric and technocratic data practices, which prioritise dominant populations in algorithmic design while failing to account for intersectional health needs.

2.1 The Structural Nature of AI Bias in Healthcare

Technoscience and technocultural studies have historically been dominated by men – not only from a scientific perspective, but also through cultural and sociological practices.[13] For example, technologies viewed through the lens of techno-cultural storytelling[14] excluded women and their bodies from the advancement of technologies. The pervasiveness of androcentricity[15] in medicine also contributes to this exclusion, highlighting the likelihood that 'ongoing discrepancies in the care of female patients'[16] do have a significant impact on patient care through the experience of female patients. However, women are not the only demographic to have traditionally been excluded in this manner. The systemic 'othering' of marginalised populations also operates within pre-existing social and medical hierarchies. This section of the article articulates how 'othering' functions as a mechanism of exclusion, constructing certain populations as deviant, invisible or secondary within dominant narratives. In AI-driven healthcare, 'othering' therefore manifests in ways that intertwine with AI biases.

Even in the twenty-first century, 'othering' continues to be a problem. Described as 'a set of dynamics, processes and structures that engender marginality and persistent inequality across any of the full range of human differences based on groups identities',[17] 'othering; is an unfortunate consequence of systemic discrimination and prejudice. While 'othering' can appear in many forms, including outward expressions of prejudice, it is also embedded in 'institutionalization and structural features'[18] where 'individual acts of discrimination have a cumulative and magnifying effect that may help explain many group-based inequalities'.[19] The manifestation of 'othering' in modern health and medicine is reflected *vis-à-vis* health inequalities, with the latter ultimately forming part of AI biases.

There are several key sources of bias in medical and healthcare AI systems (this is not an exhaustive assessment). First, bias can emerge from historical bias in medical data, rendering some populations 'invisible'.[20] Medical AI models are disproportionately trained on white, male and economically privileged datasets, rendering women, racial minorities, disabled

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[9] Smart, Feminism and the Power of Law.
[10] Benjamin, Race After Technology.
[11] Hoffman, "Racial Bias."
[12] Criado-Perez, Invisible Women.
[13] Lan, "Technofetishism of Posthuman Bodies," 166.
[14] Paxling, "Transforming Technocultures."
[15] Merone, "Sex Inequalities in Medical Research."
[16] Merone, "Exploring Androcentricity," 6.
[17] Powell, "The Problem of Othering."
[18] Powell, "The Problem of Othering."
[19] Powell, "The Problem of Othering."
[20] Criado-Perez, Invisible Women.

individuals and lower-income patients statistical outliers rather than central subjects.[21] For example, it was found that AI-driven cardiovascular risk assessments under-estimate heart disease risk in women;[22] reflecting decades of androcentric medical research that treats male physiology as the universal norm.[23] In her book *Unwell Women*, feminist cultural historian Elinor Cleghorn proclaims, in a powerful final paragraph in the introduction:

> Medicine must hear unwell women when they speak – not as females, weighed down by the myths of the man – made world, but as human beings. Medicine must listen to and believe our testimonies about our own bodies, and ultimately turn its energies, time, and money towards finally solving our medical mysteries. The answers reside in our bodies, and in the histories our bodies have always been writing.[24]

Cleghorn's masterful work presents a woeful and disturbing view of the ways in which modern medicine and healthcare continue to fail women, often dismissing and disbelieving women's symptoms of illness, disease and pain. While Cleghorn's extensive investigation into the mistreatment of women in medicine is by no means completely novel, her findings show a 'richly detailed, wide-ranging and enraging history of how conventional medicine has pathologized, dismissed and abused women from antiquity to the present'.[25]

Second, biomedical 'normativity' and algorithmic deviance is another way of ignoring racial biases in predictive models. Biomedical 'normativity' refers to the implicit standards and assumptions that define what is considered 'normal' or 'healthy' in medical science. It shapes diagnostic criteria, treatment protocols and healthcare policies, often reinforcing androcentric and Eurocentric biases. However, it has been argued that biomedical (or biological) normativity is historically constructed rather than an inherent property of life.[26] For this reason, AI systems often flag marginalised groups as 'deviant' or 'atypical' when their health indicators do not confirm to dominant biomedical standards – a further illustration of how 'othering' continues to manifest. For example, it has been shown that race-based correction factors in AI-driven kidney function assessments delay referrals for Black patients.[27] Vyas et al., in this study, examined how kidney function assessments, pulmonary function tests and cardiology algorithms systematically adjust medical risk scores based on race, often delaying or denying necessary treatment for Black patients. The study calls for the abolition of race-based adjustments, emphasising that they are not scientifically justified and perpetuate health disparities. In another study by Hoffman et al.,[28] racial biases in medical assessments of pain reveal how Black patients are systematically undertreated due to false beliefs about biological differences. The study found that half of medical students and residents believed Black patients had thicker skin or higher pain tolerance, leading to less pain medication being prescribed, compared with white patients with identical symptoms. This shows how racial myths embedded in medical systems affect AI-driven pain-management tools, perpetuating algorithmic discrimination in healthcare.

The third source of bias comes from socioeconomic perspectives, not only through the issue of access to AI-driven healthcare, but also in accessing *general* healthcare. Predictive analytics in healthcare are increasingly used to determine insurance eligibility, hospital admissions and chronic disease management, yet these models frequently mis-clarify low-income patients as 'high risk',[29] as identified by O'Neil. This leads to reduced access to preventive care and increased financial penalties. O'Neil also critiques the unchecked power of algorithms, arguing that big data models reinforce systemic inequalities rather than eliminate them. Eubanks[30] examines how automated decision-making systems in welfare, housing and child protection disproportionately target and punish low-income communities. She argues that digital tools used in public assistance programs are modern extensions of historical poverty-management strategies, reinforcing racial and economic disparities. Eubanks particularly addresses AI-driven insurance risk assessments, which disproportionately flag low-income individuals as more likely to require medical intervention. This results in higher premiums, denial of coverage, and medical debt accumulation, reinforcing structural barriers to healthcare access.

The socioeconomic 'othering' is also prevalent in AI-driven patient prioritisation. Hospitals increasingly use AI triage systems to prioritise patient care, yet socioeconomic factors are rarely accounted for in algorithmic decision-making. AI models trained

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[21] Butter, "Caroline Criado Perez."
[22] Sau, "Artificial Intelligence-Enhanced Electrocardiography."
[23] Steuernagel, "Countering Sex and Gender Bias."
[24] Cleghorn, Unwell Women, 19.
[25] Merritt, "Unwell Women Review."
[26] Miquel, "What is Biological Normativity?"
[27] Vyas, "Hidden in Plain Sight."
[28] Hoffman, "Racial Bias in Pain Assessment."
[29] O'Neil, Weapons of Math Destruction.
[30] Eubanks, Automating Inequality.

on datasets from wealthier populations often under-estimate the severity of medical conditions in low-income patients, further reinforcing the digital divide in access to healthcare.[31] As an example, AI-driven emergency room admissions models frequently deprioritise uninsured patients or those with Medicaid, categorising them as less urgent cases even when their symptoms align with high-risk indicators.

These narratives of AI bias have a direct correlation with health inequalities. These biases risk exclusion, trapping marginalised communities in cycles of poor health outcomes and financial insecurity. Rather than serving as neutral tools, AI biases automate discrimination, disproportionately targeting marginalised communities while denying equitable healthcare interventions. In accordance with the fundamental tenets of this article, Eubanks warns that algorithmic governance is not neutral, calling for human-centred policy reforms.[32]

2.2 The Dominant Legal Narrative of AI Bias

Law has always been more than rules: it is a storytelling device, a tool for shaping reality rather than simply describing it. As Sherwin argues, legal discourse functions as a frame, one that dictates who is seen, who is invisible, and what counts as truth.[33] These frames do not emerge in isolation, as they are historically contingent, shaped by dominant ideologies and institutional power structures.

2.2.1 Bias and Affirmative Postmodern Storytelling

In the case of AI bias, the dominant legal narrative follows a predictable arc, constructing discrimination as a technical malfunction rather than a systemic injustice woven into the fabric of healthcare data itself. This framing aligns with what Sherwin describes as 'affirmative postmodern storytelling', where law acknowledges complexity but ultimately reinforces dominant cultural myths. The EU AI Act exemplifies this approach, categorising AI systems based on risk levels (Article 6), requiring bias audits (Article 10) and mandating transparency disclosures (Article 13) – all measures that treat bias as an issue to be fine-tuned rather than a structural consequence of exclusionary data practices.

Sherwin's affirmative postmodernism helps to reveal why regulatory frameworks often fail to address bias at its roots. He argues that postmodern legal narratives can take two forms. The first, sceptical postmodernism,[34] rejects the possibility of objective truth, leading to fragmented and inconclusive legal reasoning. The second form, affirmative postmodernism,[35] embraces complexity while maintaining coherence, using cultural myths, metaphors and familiar character types to create meaning. It appears that the EU AI Act adopts an affirmative postmodern approach, recognising bias while framing it as a solvable technical issue (but also not clearly providing guidance as to what may constitute bias or how it is to be assessed); this is a narrative of control rather than disruption. This allows AI developers and policy-makers to retain authority over algorithmic fairness, positioning bias as a predictable defect that can be optimised away through audits and procedural safeguards. But bias is not merely a glitch: it is embedded in the historical exclusions of medical AI, the privileging of androcentric research and the socioeconomic stratifications of healthcare access.[36]

A compelling historical example of affirmative postmodernism in legal narratives can be seen in the US Civil Rights Act of 1964.[37] While the Act marked a legislative milestone by outlawing racial segregation and discrimination, its implementation reflected a narrative of inclusion that preserved existing hierarchies. The law acknowledged racial injustice, but did not directly challenge the economic and structural foundations of racial inequality, such as housing segregation, wealth disparities and exclusion from political power. Legal compliance was framed as sufficient – businesses, institutions and government entities were required to integrate without fundamentally altering the systemic conditions that produced racial disparities in the first place.

Much like the EU AI Act's approach to bias audits, the Civil Rights Act's narrative of progress celebrated inclusivity while leaving the deeper architectures of discrimination largely intact. AI governance today mirrors this postmodern legal pattern, acknowledging bias through risk-management frameworks while avoiding direct confrontation with the exclusionary systems that generate algorithmic discrimination in healthcare, hiring, and predictive policing.

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[31] Vyas, "Hidden in Plain Sight."
[32] Eubanks, Automating Inequality.
[33] Sherwin, "Law Frames," 50.
[34] Sherwin, "Law Frames," 69.
[35] Sherwin, "Law Frames," 72.
[36] Criado-Perez, Invisible Women.
[37] Civil Rights Act of 1964.

Hence, this article challenges the EU AI Act's risk-based storytelling approach, arguing that AI bias is not simply a technical anomaly; it is a product of legal narratives that sustain exclusion. A data feminist approach (as proposed in this article) would require reframing AI bias as a structural issue, ensuring that regulatory narratives do not merely acknowledge bias, but actively intervene in the power structures that sustain it. Just as Sherwin critiques the law's tendency to transform complex injustices into manageable narratives,[38] AI governance must resist the pull of technocratic storytelling, recognising that algorithmic bias demands structural transformation much more than compliance.

2.2.2 Formalist Bias Framing in the EU AI Act

The EU AI Act constructs a formalist legal narrative of AI bias – one that situates bias as a correctable flaw rather than an embedded structural issue. This framing aligns with what Sherwin describes as a formalist legal posture, where law is positioned as an objective mechanism for resolving disputes without acknowledging its own role in shaping social realities. This article highlights three specific obligations in the EU AI Act that exemplify formalist bias framing (these obligations are not intended to be exhaustive), which presupposes the mitigation of bias through technical safeguards instead of looking towards structural inequalities that shape algorithmic outcomes.

The Act's approach to bias mitigation reflects a technocratic governance model,[39] assuming that algorithmic fairness can be achieved through risk classification, transparency measures and bias audits. However, this approach fails to account for historical exclusions, intersectional inequalities and androcentric assumptions embedded in AI systems.[40] The EU AI Act primarily addresses technical safeguards as follows: first, through risk classification to determine the level of regulatory scrutiny required by an AI system (Title III, Chapter 2, Article 6); second, through bias audits to access whether AI systems produce discriminatory outcomes (Title III, Chapter 2, Article 10); and finally, in relation to transparency requirements for AI developers to disclose how algorithms function (Title III, Chapter 2, Article 13).

While these measures aim to mitigate bias, they reflect a formalist legal posture that assumes discrimination can be resolved through technical corrections rather than structural reform. Section 4 will further critically analyse each of these 'safeguards'.

2.3 Data Feminism as a Counter-Narrative

In consideration of the foregoing sections, this article argues for data feminism as a counter-narrative to dominant legal narratives of AI bias in its governance framework. This will also be further elaborated upon in section 4. It is contended that data feminism that employs intersectionality discourse can develop 'an empathetic approach to experiences and narratives of privilege within healthcare'.[41] A data feminist approach to AI regulation necessitates a shift from risk mitigation to equity-based intervention, ensuring that governance frameworks do not merely acknowledge bias, but actively dismantle exclusionary logics. Regulatory mechanisms must move beyond statistical fairness checks[42] and intervene at the level of the epistemological foundations of AI knowledge production, addressing how medical datasets, legal classifications and predictive models are constructed in the first place.[43] Rather than treating bias as a technical problem that is solvable through compliance, AI governance must embrace structural justice, challenging the dominant narratives that position AI as an ethically neutral tool rather than a system embedded with historical inequities.

3. Androcentricity and Intersectionality in AI Governance

Androcentricity – the privilege of male-centred perspectives in knowledge production – has long shaped medical research, technological development and legal frameworks. It is relevant in contemporary AI governance discourse because its persistence has shaped AI development, regulation and deployment, often reinforcing gender biases in data, algorithms and policy frameworks. Coined by Charlotte Perkins Gilman,[44] the concept of androcentricity, which is based on the perspective that emphasises male experiences and viewpoints as the standard, has long influenced a variety of academic and social discussions. This male-centred perspective not only pushes women and individuals who identify as non-binary to the margins but also reinforces gender disparities in the realms of language and communication.

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[38] Sherwin, "Law Frames," 42.
[39] Behr, "Technocracy."
[40] Lau, "AI Gender Biases," 253.
[41] Lau, "The FemTech Jacquerie," 236.
[42] Hoffman, "Racial Bias in Pain Assessment."
[43] D'Ignazio, "The Seven Principles."
[44] Gilman, The Man-Made World.

Androcentricity is particularly observable in the latter part of the twentieth century, when medical trials were largely conducted with male participants, thus disregarding the distinct physiological and psychological characteristics of female individuals.[45] This kind of practice contributed significantly to a widespread fallacy that the health issues faced by women could be extrapolated from male data, resulting in sub-par treatment protocols. For example, in Jerry Pinto's *Em and the Big Hoom* (2012),[46] the complexities tied to the experience of mental illness – especially regarding women – are frequently masked by societal expectations that tend to pathologise their emotional states instead of recognising them as essential components of their lived experiences.[47]

Legal systems, too, have historically been androcentric, constructing male-centred epistemologies that shape governance frameworks. As Carol Smart argues, law does not merely reflect social reality;[48] it actively constructs gendered hierarchies, privileging male-coded rationality while marginalising women's lived experiences. Smart challenges the assumption that law is neutral, arguing that legal discourse is deeply embedded in patriarchal knowledge production. She critiques the legal construction of "the woman",[49] showing how law frames women's experiences through male-defined categories, often reducing gendered oppression to procedural inefficiencies rather than structural injustices.[50]

3.1 Historical Androcentric Bias in Health and Medical AI

In the context of health and medical AI, both in deployment and governance, androcentrism continues to persist because medical AI systems inherit biases from historical medical research, where male bodies have been treated as the default standard for diagnosis and treatment.

In reproductive healthcare, legal frameworks often prioritise biomedical expertise over embodied knowledge, sidelining women's autonomy in medical decision-making.[51] AI-driven FemTech applications, designed with androcentric regulatory models, frequently fail to account for intersectional disparities, reinforcing gendered exclusions in algorithmic healthcare diagnostics.[52] The exclusion of women from research studies has culminated in a significant shortage of female representation in studies that influence treatment protocols, even though women possess distinct physiological and psychological characteristics. This deficiency not only hinders the process of making accurate diagnoses but also perpetuates a deep-seated scepticism towards the healthcare system.[53] This scepticism is highlighted by accounts from women experiencing chronic illnesses, who frequently state that their symptoms are often dismissed or minimised by medical professionals.[54]

The absence of research methodologies that are sensitive to gender further intensifies existing health disparities, highlighting an urgent requirement for extensive research that takes into consideration the differences associated with sex and gender in both biological and sociocultural frameworks.[55] As a result, healthcare interventions frequently do not consider how aspects related to gender influence the manifestation of diseases and the effectiveness of treatments, thus worsening existing health inequalities. Additionally, the incorporation of AI in healthcare, which often reflects male-oriented datasets, creates algorithms that could unintentionally sustain gender disparities, thus provoking ethical dilemmas regarding the careful advancement of health technologies.[56]

The representation deficit within health-relevant datasets significantly amplifies the impediments introduced by inherent algorithmic inclinations in medical AI systems, consequently reinforcing the long-standing inequities deeply embedded within the frameworks of healthcare provisions. Sub-groups, particularly racial and ethnic minorities, members of the LGBTQ+ community and individuals experiencing disabilities, are frequently either omitted or insufficiently encapsulated within health-relevant data pools.[57] This results in the creation of algorithmic formulations that fail to encompass their distinct medical necessitation and life experiences adequately. Such systemic non-inclusion of societal groups further magnifies the disparities prevalent in diagnostic, therapeutic and health outcome domains. The imperative to redress this is critical for ensuring we have

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[45] Merone, "Exploring Androcentricity."
[46] Thomas, "Em and the Big Hoom by Jerry Pinto."
[47] Das, "Female Body-Corporeal."
[48] Smart, Feminism and the Power of Law, 4.
[49] Smart, Feminism and the Power of Law, 96–97.
[50] Smart, "The Woman of Legal Discourse."
[51] Lau, "AI Gender Biases," 252.
[52] Lau, "The FemTech Jacquerie," 231.
[53] Criado-Perez, Invisible Women.
[54] Merone, "Exploring Androcentricity."
[55] Gemmati, "Bridging the Gap."
[56] Lau, "The FemTech Jacquerie," 230.
[57] Lau, "The Impact of AI-Driven Technologies."

ethically reliable and efficient AI-driven systems, purposed to dispense equitable healthcare solutions indiscriminately across diverse identity spectrums or backgrounds.[58]

While the issue of algorithm bias is not completely new, the use of AI in machine learning and in diagnosis protocols, for example, can be problematic. The most concerning issue in the use of AI algorithms for cardiovascular disease diagnosis is clearly articulated as follows:

> Women and minority groups are historically under-represented in cardiology, and the bulk of current evidence-based medicine might not necessarily apply to these populations. A systematic review of 207 trials found consistent under-reporting of female and Black patients from 2001 to 2018. Although the same proportion of women and men present with chest pain, men are 2·5 times more likely to be referred to a cardiologist for management than women.7 Black patients in the emergency room are 40% less likely to receive pain medication than White patients. These inequalities are preserved in troves of health data, which are being used to train AI algorithms. Obermeyer and colleagues found that use of a widely used commercial prediction algorithm resulted in significant racial bias in predicting outcomes. Specifically, the algorithm identified White patients to have higher risk scores and were more often selected to receive additional care than Black patients who were equally as sick. In a study by Nordling and colleagues, a machine learning algorithm identified the patient's postcode as the number one predictor for prolonged hospital stay, correlating to areas of low income and predominantly Black neighbourhoods. From these findings, another ethical dilemma arises in using an algorithm for decision making. If the algorithm was designed to optimise hospital resources, high-income White patients might be selected to receive the majority of hospital resources, further deepening the divide in access to care for minority and underserved groups.[59]

In cancer treatment, for example, researchers at the University of Chicago have found that deep learning models trained on extensive cancer genetic and tissue histology data can easily identify the institution that submitted the images.[60] These models, which use machine learning to recognise specific cancer signatures, often rely on the submitting site as a shortcut for predicting patient outcomes. This approach groups all patients from the same site together, rather than considering the unique biology of each patient.[61]

This flaw in the algorithm could result in biases and missed treatment opportunities, particularly for patients from racial or ethnic minority groups who are already under-represented and face challenges in accessing care.[62] According to Alexander Pearson, a co-senior author of the study and Assistant Professor of Medicine at University of Chicago Medicine:

> [We] identified a glaring hole in the in the current methodology for deep learning model development which makes certain regions and patient populations more susceptible to be included in inaccurate algorithmic predictions.[63]

The repercussions of biased computational formulae continue to significantly echo for health and medical AI, continuing the propagation of discrepancies concerning both diagnostic precision alongside therapeutic results, especially within groups that are less represented or more marginalised. As biases within algorithms endure in shaping the modality of healthcare provisioning, an urgent necessity emerges to embrace an AI schematic endowed with conscientiousness, one that venerates transparency, equity and accountability, as heralded within ethical paradigms and global directives.

3.2 Intersectionality and AI Bias

This section argues that Kimberlé Crenshaw's intersectional framework provides a crucial lens for understanding how AI bias operates within legal narratives. A term coined by Crenshaw in 1989, intersectionality is 'a metaphor for understanding the ways that multiple forms of inequality or disadvantage sometimes compound themselves and create obstacles that often are not understood among conventional ways of thinking'.[64] However, the concept itself predates Crenshaw, with Black feminist literature, such as the Combahee River Collective's 1977 'A Black Feminist Statement',[65] already addressing the interconnectedness of race, gender and other social identities. Intersectionality remains a crucial analytical framework for understanding and addressing social inequalities, influencing academic research and driving societal and policy changes.[66]

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[58] Lau, "Stakeholder Joint Statement."
[59] Tat, "Addressing Bias."
[60] McNemar, "Detecting Artificial Intelligence Algorithm Bias."
[61] McNemar, "Detecting Artificial Intelligence Algorithm Bias."
[62] McNemar, "Detecting Artificial Intelligence Algorithm Bias."
[63] "Artificial Intelligence Models."
[64] Crenshaw, "Demarginalizing the Intersection."
[65] Womack, "The Combahee River Collective."
[66] Lau, "AI Gender Biases."

In contemporary health discourse, the omission of intersectionality often leads to a fragmented understanding of well-being across diverse populations. Intersectionality, a framework that acknowledges the interconnected nature of social categorisations such as race, gender and socioeconomic status, serves as a crucial lens through which to analyse health disparities. By neglecting this multifaceted perspective, public health strategies may inadvertently reinforce systemic inequalities, undermining efforts to address the unique needs of marginalised groups. An exploration of the negative ramifications of this oversight reveals not just gaps in research but real-world consequences that exacerbate health inequities. Establishing a comprehensive approach that incorporates intersectional considerations is essential for advancing health equity and fostering inclusive practices.

The concept of intersectionality is critical for understanding health outcomes, as it examines how overlapping social identities – such as race, gender and socioeconomic status – interact to shape individual experiences and access to healthcare.[67] Neglecting this framework can lead to a narrow view of health disparities, obscuring the complexities of how systemic inequalities manifest in healthcare settings. For instance, the experiences of informal caregivers – particularly those with migration backgrounds – are often overlooked, resulting in limited support and recognition within care networks.[68] These caregivers face unique challenges that are exacerbated by their social positioning and cultural contexts, highlighting the necessity for diversity-responsive policies to better address their needs. Similarly, social determinants such as community support and societal structures can influence pain management, emphasising that a multifaceted approach to health – integrating personal and social factors – is crucial for equitable healthcare outcomes.[69]

In health and medical AI, health disparities are exacerbated when the concept of intersectionality is overlooked, as individuals with intersecting social identities often face compounded health risks. The interplay between race, gender, socioeconomic status and other factors creates unique vulnerabilities that cannot be fully understood through a singular lens. For example, Black women face not only the challenges of gender bias but also the systemic inequalities associated with race, leading to significantly higher rates of maternal mortality compared with their white counterparts.[70] Such disparities highlight the need for an intersectional approach in health research and policy formulation that acknowledges the complexity of identities and their combined effects on health outcomes. By failing to consider these interconnected dimensions, health interventions may not only be ineffective but could further entrench inequality.[71]

3.3 Intersectionality and Dimensions of Discrimination in the EU AI Act

An intersectionality framework provides a crucial lens for understanding how AI bias operates within legal narratives, particularly in the EU AI Act. Intersectionality captures three dimensions of discrimination: structural intersectionality (how institutions reinforce inequalities); political intersectionality (how marginalised groups are excluded from policy discourse); and representational intersectionality (how narratives shape perceptions of identity and justice). The following sections explore how the EU AI Act engages with these dimensions of intersectional discrimination. This evaluation lends support to the article's justification of reframing AI bias as a structural problem.

3.3.1 Structural Intersectionality

Structural intersectionality refers to deeply embedded inequalities within institutions, policies and social systems that systematically disadvantage marginalised groups. Unlike individual discrimination, which occurs on a case-by-case basis, structural discrimination is woven into the fabric of legal, economic and technological frameworks, making exclusion self-reinforcing and difficult to dismantle. Crenshaw argues that legal frameworks and systems often fail to account for compounded discrimination, treating race and gender as separate categories rather than interconnected experiences. This oversight leads to policy failures, where laws designed to address bias do not fully protect those at the intersection of multiple marginalised identities.

Examples of structural discrimination can be found in relation to healthcare disparities, many of which have already been highlighted in the preceding sections of this article These examples include situations where medical AI systems misdiagnose Black patients at higher rates, or where FemTech applications fail to account for reproductive health disparities among women of colour. It is also present in employment and economic inequality, and in predictive policing and surveillance. Structural discrimination in the EU AI Act is exemplified through the treatment of AI biases as technical flaws. Obligations under Article

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[67] Kelly, "'Doing' or 'Using' Intersectionality?"
[68] Hengelaar, "A Sense of Injustice."
[69] Kapos, "Social Determinants."
[70] Lister, "Black Maternal Mortality."
[71] Bey, "Health Disparities."

6 (risk-based classification) or Article 10 (bias audits) fail to address how structural inequalities shape algorithmic decision-making and do not interrogate the epistemological foundations of AI bias.

3.3.2 Political Intersectionality

This article argues that political discrimination in AI governance occurs when legal frameworks privilege dominant power structures, sidelining marginalised voices in policy-making.[72] The EU AI Act, while aiming for fairness, has been critiqued for reinforcing technocratic governance, where corporate and state interests, rather than community-led interventions, shape AI regulation.

While the EU AI Act's consultation process included stakeholder engagement, feminist and intersectional perspectives were not systematically integrated. Feminist scholars and advocacy groups pushed for gender-responsible AI governance, but their recommendations were not fully incorporated into the final legislative framework. A feminist AI collective and DATAWO[73] proposed six action points for a feminist-informed AI Act, emphasising inclusive datasets, intersectional bias audits and participatory governance, but these were not prioritised in the final Act.[74] A report by the Centre for European Policy Studies (CEPS) found that industry stakeholders accounted for 47.2 per cent of responses to public consultation, while citizen participation remained limited at 5.74 per cent.[75] Tech corporations and AI developers had greater influence in shaping regulatory guidelines while grassroots organisations advocating for marginalised communities had minimal representation.

To this end, it is not surprising to see how this dimension of discrimination has manifested in the EU AI Act – for example, resulting in bias audits (Article 10) that do not require intersectional evaluations and only focus on statistical fairness. The lack of public transparency (Article 13), in allowing private entities to conduct internal bias audits without external scrutiny, appears to prioritise corporate compliance over public accountability. Civil society organisations and digital rights groups have raised concerns that the Act therefore does not adequately protect against algorithmic discrimination in public services.[76]

3.3.3 Representational Intersectionality

As theorised by Crenshaw, representational intersectionality refers to the ways in which marginalised identities are depicted – or erased – within dominant narratives, in the media and in legal discourse. It highlights how stereotypes, cultural framing and institutional biases shape public perceptions, reinforcing exclusionary structures. Crenshaw argues that representation is not merely symbolic: it has material consequences, influencing policy decisions, legal protections and access to justice.
Ruha Benjamin's scholarship extends Crenshaw's critique to AI, demonstrating how algorithmic bias operates through invisibility and misrepresentation.[77] For example, facial recognition systems misclassify Black individuals at higher rates, reinforcing racialised surveillance.[78] AI-driven hiring algorithms penalise women and racial minorities, embedding androcentric and Eurocentric labour hierarchies. Predictive policing tools disproportionately target Black and Latinx communities, replicating historical patterns of racial profiling.

Consequently, the EU AI Act mirrors these representational failures, as demonstrated above with examples relevant to Article 10 (bias audits), Article 13 (transparency), and Article 6 (risk-based classification). Collectively, the architecture of these provisions in the Act dismiss the notion of structural interventions, sweeping systemic injustice into the cracks of the algorithmic code.

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[72] Lau, "Stakeholder Joint Statement."
[73] Karagianni, "EU AI Act Policy Paper."
[74] Wudel, "A Feminist Vision for the EU AI Act."
[75] "European Commission Releases Analysis of Stakeholder Feedback."
[76] Lau, "Stakeholder Joint Statement."
[77] Benjamin, Race After Technology.
[78] Buolamwini, "Gender Shades."

4. Data Feminism as a Counter-Narrative to the EU AI Act

Section 2.3 provided a precursor to the argument that data feminism can serve as a counter-narrative to dominant legal narratives of AI bias in its governance framework. To do so, this section challenges the formalist bias framing (the legal narrative of AI bias) in the EU AI Act, and subsequently, explores the key principles of data feminism and its application to AI regulation.

4.1 Challenging the Formalist Bias Framing in the EU AI Act

The first frame of challenge is the risk-based classification of AI systems in the EU AI Act. The EU AI Act categorises AI systems based on their potential harm: Article 6 of the Act establishes the classification rules for high-risk AI systems. This article argues that this risk-based classification appears to prioritise financial or security concerns. Indeed, the EU AI Act presents harmonised rules for the market placement and use of AI in the European Union.[79] Under the Act, an AI system is classified as high risk if it is explicitly listed in Annex III of the Act, or if it is intended to be used as a safety component in regulated products. Hence, providers of high-risk AI systems must comply with strict regulatory requirements (Article 8), including risk management (Article 9), data governance (Article 10), technical documentation (Article 11), record-keeping (Article 12), transparency (Article 13), human oversight (Article 14) and accuracy, robustness and cybersecurity (Article 15). It is particularly noteworthy that AI systems with significant societal impact must also undergo rigorous assessment under the Act before they are being deployed.

The problem with this classification is that health-related AI applications that affect marginalised groups receive less scrutiny than AI used in financial or security contexts. Olofsson et al[80] argue that risk discourse is often used as a governance tool, framing social problems in terms of risk management rather than structural injustice. Risk-management practices create new divisions, reproducing existing forms of social inequality: gender, race, class, and other social categories shape the lived experience of risk,[81] with social institutions redefining marginalised groups as 'risky' populations[82] so they may reinforce exclusion through governance strategies. Lau additionally questions the fact that AI-driven women's health diagnostics, more commonly known as 'FemTech', are not classified as high risk, despite their potential to reinforce gendered health disparities.[83]

The second formalist bias frame in the EU AI Act that is challenged concerns bias audits without intersectional considerations. Article 10, regarding data and data governance, specifically addresses bias and bias audits within AI systems, outlining requirements for high-risk AI systems to ensure training, validation and testing datasets are representative, error-free and free from discriminatory biases. However, this article argues that bias audits, which are aimed at detecting and mitigating algorithmic discrimination, often operate as technical safeguards rather than structural interventions. They fail to address the deeper exclusions embedded in AI systems.[84] These audits rely on quantitative fairness metrics that obscure intersectional disparities, treating bias as a statistical error rather than a reproductive mechanism of systemic inequality.[85] Furthermore, bias audits frequently prioritise regulatory compliance over ethical accountability, allowing developers to optimise risk classification without challenging the androcentric and technocratic foundations of AI governance.[86] Potentially, the lack of public transparency in bias audits, where companies conduct internal assessments without disclosing methodologies, reinforce power asymmetries, making AI bias a controlled narrative rather than a site for structural transformation.[87] An AI model may pass a bias audit if it achieves equal accuracy across male and female patients, but the audit does not account for how bias manifests differently across racial, socioeconomic, and gender intersections.

A challenge to the third frame of formalist bias framing in the EU AI Act can be found in the obligation for transparency in Article 13, which this article claims acts as a substitute for structural change. The Act mandates that AI developers provide explanations for how their systems make decisions. However, transparency alone does not eliminate bias; it merely makes bias more visible.[88] Phan and Wark examine how race is operationalised in AI models without explicit racial markers, meaning that bias persists even when race is not directly encoded. This phenomenon, known as proxy discrimination, allows AI systems to replicate historical exclusions under the guise of neutrality. For example, an AI-driven diagnostic tool may disclose that it

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[79] Lau, "The FemTech Jacquerie," 234.
[80] Olofsson, "The Mutual Constitution."
[81] Olofsson, "The Mutual Constitution," 8–9.
[82] Olofsson, "The Mutual Constitution," 10.
[83] Lau, "The FemTech Jacquerie," 233.
[84] Crenshaw, "Demarginalizing the Intersection."
[85] Shelby, "Whiteness in and Through Data Protection."
[86] Smart, Feminism and the Power of Law.
[87] Vyas, "Hidden in Plain Sight."
[88] Phan, "Racial Formations."

under-diagnoses heart disease in women – but the Act does not require structural interventions to address the underlying biases in medical research that led to this disparity.

Ultimately, the EU AI Act's procedural safeguards operate within a formalist paradigm that needs to be dismantled. Bias is not simply a correctable technical error: this article has demonstrated that it is a structural consequence of exclusionary knowledge production. A continuation of these existing regulatory mechanisms risk perpetuating inequities under the guide of compliance if we do not take the necessary steps to interrogate the underlying androcentric, racialised and neoliberal logics embedded in AI governance.

4.2 Key Principles of Data Feminism and its Application to AI Regulation

Lau states that 'in an idealised world, intersectionality and data feminism may be one of the solutions to address algorithm biases … with the core of the theory providing specific strategies to data scientists in working towards attaining ethical, equitable, equal data justice'.[89] Data feminism provides a structural critique of androcentric data practices, demonstrating how AI systems inherit biases from historical exclusions in medical research and healthcare access. It emphasises examining the root causes of bias rather than merely correcting algorithmic outputs; centring marginalised voices in AI governance; and recognising that bias is not an isolated error, but a structural issue embedded in historical inequalities.

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[89] Lau, "The FemTech Jacquerie," 237.

In Table 1, each of the seven principles of data feminism[90] is described, with justification that challenge the conventional notions of bias mitigation and fairness in AI regulation and denotes what implications there may be for AI governance.

Table 1. The principles of data feminism and its implication for AI governance

No.	Principle(s)	Examples	Implication for AI governance
1	**Examine power** This requires an interrogation into who controls data and AI development. Data are shaped by power relations, historical inequalities and dominant epistemologies. Data feminism argues that AI systems must not only audit bias but critically examine the power structures that sustain algorithmic exclusion.	• Algorithmic bias in facial recognition technologies: the Gender Shades study found that leading facial recognition systems had error rates of up to 34.7 per cent for dark-skinned women, compared with less than 0.8 per cent for white men. • These errors have led to wrongful arrests, based on flawed AI-driven police identification. • The development of AI-driven facial recognition is largely controlled by tech corporations and law enforcement agencies, with minimal public oversight or regulation.	• Article 6 (Risk-Based Classification) acknowledges high-risk AI systems but does not mandate power redistribution in AI governance. • Article 13 (Transparency Requirements) requires AI disclosure but does not ensure participatory oversight for affected communities. • Solution: A data feminist approach would require community-led AI regulation, shifting decision-making power to those most affected by algorithmic bias.
2	**Challenge power** This requires regulatory systems to not only acknowledge bias but actively challenge exclusionary knowledge production.	• Medical AI systems often fail to diagnose cardiovascular diseases in women, reinforcing androcentric medical bias. • Historically, medical research prioritised male-centric symptomatology, leading AI systems to under-diagnose heart attacks in women. • The Apple Health app initially launched without a menstrual cycle tracker, reflecting gendered exclusions in digital health innovation.	• Bias audits mandated in Article 10 focus on dataset fairness but do not interrogate androcentric medical epistemologies. • Solution: AI regulation must move beyond compliance-driven fairness metrics and engage with feminist critiques of healthcare data governance.
3	**Elevate marginalised voices** AI governance must prioritise the knowledge and experiences of those most affected by algorithmic bias. An intersectional perspective should shape bias audits, transparency measures, and policy frameworks. This centres community-led AI regulation.	• Indigenous communities have long challenged extractive data practices, where corporations collect and exploit Indigenous data without consent. • Google's Project Maven, a military AI initiative, used Indigenous land-mapping data without transparent agreements. • Health AI systems trained on western biomedical models often fail to recognise Indigenous healing practices, reinforcing epistemic exclusions in medical AI governance.	• The EU AI Act does not mandate Indigenous or intersectional participation in AI regulatory decision-making. • Solution: AI governance should integrate data sovereignty protections, ensuring that marginalised communities retain control over their data.
4	**Rethink binary systems** Traditional AI governance relies on binary classifications, erasing fluidity and nuance in human identities. Data feminism advocates for relational, intersectional approaches to algorithmic fairness by rejecting fixed categories in AI decision-making.	• AI-driven gender classification systems often fail to recognise non-binary and transgender identities, reinforcing binary epistemologies in algorithmic governance. • The US Department of State's digital passport system now only allows "male" or "female" selections, excluding non-binary individuals from digital identity verification. • AI-powered hiring software often misgenders trans applicants, leading to discriminatory hiring outcomes.	• The EU AI Act's fairness assessments rely on fixed demographic categories, failing to address fluidity in gender and racial classification. • Solution: AI systems should incorporate participatory, adaptive modelling, ensuring inclusivity beyond binary fairness metrics.

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[90] D'Ignazio, "The Seven Principles."

No.	Principle(s)	Examples	Implication for AI governance
5	**Embrace complexity** Bias audits often reduce discrimination to numerical fairness metrics, masking deeper epistemological exclusions. Data feminism calls for qualitative, participatory mechanisms to account for algorithmic bias.	• Credit scoring algorithms penalise low-income individuals, disproportionately affecting women and racial minorities. • AI-driven loan approval models use historical banking data, which reflects systemic exclusion of women and marginalised communities from financial services. • Even when bias audits correct statistical disparities, these systems still reinforce economic discrimination.	• Bias audits in Article 10 fail to account for compounded financial exclusions, reinforcing economic inequalities. • Solution: AI regulation must move beyond formal fairness checks, integrating structural financial justice into algorithmic bias assessments.
6	**Make data work for justice** It is imperative to ensure that AI serves the needs of marginalised communities. Regulatory systems should not merely mitigate harm but also actively promote equity.	• FemTech applications often exclude marginalised reproductive health experiences, reinforcing androcentric medical governance. • AI-powered fertility trackers do not account for PCOS, menopause, and reproductive health disparities among women of colour, failing to provide equitable health interventions. • Data governance in reproductive health often prioritises commercial interests over user autonomy and privacy protections.	• Bias audits in Article 10 of the EU AI Act do not mandate reproductive health equity in AI datasets. • Solution: AI governance should prioritise equity-based healthcare interventions, ensuring data transparency, consent, and intersectional medical representation.
7	**Recognise that data science is never neutral** AI systems do not operate in isolation, as they reflect historical, cultural and institutional biases. Data feminism advocates for the challenging of AI's false objectivity.	• Predictive policing algorithms target Black communities disproportionately, embedding racialised assumptions into law enforcement AI governance.	• The EU AI Act does not mandate anti-racist accountability frameworks, reinforcing racial exclusions in algorithmic risk assessment. • Solution: AI governance should incorporate abolitionist critiques, ensuring that data-driven systems actively dismantle systemic oppression.

These seven principles of data feminism provide a critical blueprint for rethinking AI governance, demanding a shift from procedural fairness to structural justice and participatory accountability. Moving beyond compliance-driven regulations to the active interrogation of systemic exclusions is a crucial approach in dismantling the epistemological foundations of bias.

4.3 Constructing an Alternative AI Governance Narrative with Data Feminism

This article contends that there is a need to shift the formalist legal narrative of AI bias into an alternative AI governance narrative, a regulatory framework that embraces data feminism, integrating policies that challenge androcentric epistemologies, racialised surveillance and economic exclusion. The privilege of technocratic compliance is rejected in favour of systemic accountability. In Table 2, four key policy considerations are identified (although this is not an exhaustive list), which would assist in shifting the AI governance narrative.

Table 2. Policy considerations and recommendations for alternative AI governance

No	Policy	Recommendation	Proposed Implementation
1	Mandating intersectional bias audits beyond statistical fairness	Require intersectional bias evaluations that go beyond fairness metrics. These should incorporate qualitative assessments that examine how AI systems encode structural inequalities.	AI providers must engage independent intersectional oversight boards, ensuring that bias audits interrogate gendered, racialised and economic exclusions in algorithmic decision-making.
2	Embedding data sovereignty in AI governance	Implement data sovereignty mechanisms in AI governance, requiring consent-based data collection, with protections for Indigenous, racialised and gendered communities.	AI governance and authoritative bodies must establish participatory regulatory frameworks where affected communities can co-author AI policies and monitor compliance.
3	Redefining high-risk AI beyond formalist classifications	Embed high-risk AI classifications to include structural bias assessments, ensuring that the systems used are evaluated through participatory oversight.	AI regulators must shift from binary risk assessments to continuous equity-driven evaluations, requiring public transparency in algorithmic accountability reporting.
4	Ensuring transparency and public accountability in AI decision-making	Require public access to AI audits, governance reports and fairness assessments, ensuring civil society organisations, feminist scholars and affected communities have oversight.	Governments must establish open-access AI regulatory databases, where algorithmic governance is reviewed and challenged by intersectional legal experts.

In addition, this article aligns with feminist legal critiques, articulated via the scholarship of Carol Smart, Catherine MacKinnon, Kimberlé Crenshaw and Martha Fineman, amongst others; and challenges the EU AI Act's formalist approach to bias mitigation, arguing that the Act fails to interrogate the structural, political, and representational inequalities embedded in AI systems. For example, Smart critiques law's false neutrality[91] and highlights how androcentric legal epistemologies mask gendered exclusions. This is a critique mirrored in bias audits (Article 10) of the EU AI Act that treats fairness as a procedural safeguard rather than a site for structural intervention. MacKinnon argues that formal equality principles reinforce patriarchal governance;[92] this article argues that this is evident in AI hiring algorithms that perpetuate workplace gender hierarchies. Meanwhile, Crenshaw exposes intersectional blind spots in legal frameworks,[93] which have been extensively mapped out in the preceding sections of this article. Additionally, Fineman's vulnerability theory[94] critiques neoliberal regulatory models that privilege market-driven compliance over substantive justice, validating this article's argument that risk-based classification of AI systems (Article 6) in the EU AI Act prioritises corporate AI ethics rather than systemic redistribution of protections.

Hence, a data feminist approach to AI regulation, transformed into a new AI governance narrative as demonstrated, can assist in ensuring that governance frameworks actively dismantle exclusionary logics beyond the mere acknowledgement of bias. Embedding policy interventions grounded in intersectional justice, data sovereignty and participatory governance is critical for ensuring that AI regulation also serves the needs of marginalised communities.

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[91] Smart, Feminism and the Power of Law.
[92] MacKinnon, Feminism Unmodified, 2–3.
[93] Crenshaw, "Mapping the Margins."
[94] Fineman, "The Vulnerable Subject."

5. Conclusion

The integration of health AI systems poses significant ethical considerations and regulatory challenges that must be rigorously addressed to ensure patient safety and promote equitable access to care. It is already known that machine learning models may inadvertently reflect societal biases and perpetuate health disparities if not properly monitored and regulated. While AI presents opportunities for innovation in drug development, regulatory frameworks have yet to keep pace with these advancements. Current guidance mechanisms remain inadequate, as highlighted by the need for regulatory authorities to establish appropriate oversight protocols that safeguard public welfare and streamline processes within the drug development life-cycle.[95] It is also clear that the EU aims to position itself as a normative power, shaping global standards for AI that prioritise human-centric approaches, which is critical for ensuring ethical AI implementation in health systems.[96] However, these efforts are simply not inclusive enough.'

Taking inspiration from Lau's 'ecosystem of interconnectedness"[97] for evolving frontier technologies such as the Metaverse and quantum technologies, and applying such an idea of an ecosystem to the governance of health and medical AI,[98] concerted joint efforts are necessary. The implementation of stringent data governance measures, the adoption of inclusivity-oriented data accrual methodologies and the assimilation of AI models attentive to intersectionality are critical strategies designed to counteract these biases and elevate the voices that are traditionally marginalised within healthcare research and policy-making schemes.[99] Implementing data feminism encourages and validates a recognition that achieving true equality means needing to examine the root causes of inequalities that are particularly faced by intersectional groups.[100] Such endeavours align with the imperatives of trustworthiness, transparency and accountability, deemed crucial in the progressive pursuit of equitable health AI. Without this awareness, health inequalities are bound to be exacerbated.

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[95] Nene, "Evolution of Drug Development."
[96] Brandão, "The European Union Narrative."
[97] Lau, "The Murky Waters of the Metaverse."
[98] Pidun, "The Untapped Potential of Ecosystems."
[99] Lau, "AI Gender Biases."
[100] D'Ignazio, "The Seven Principles."

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