FEMINISM AND ALGORITHMIC BIAS: REIMAGINING GENDER JUSTICE IN THE AGE OF ARTIFICIAL INTELLIGENCE

Heenal Arvind Jain &Aayushi Deepak Dhanuka, KES Shri' Jayantilal H. Patel Law College

ABSTRACT

The following paper examines the connection between algorithmic decision-making and feminist legal theory by analyzing the potential impacts that AI technologies might have on existing gender inequalities. Even though algorithms are often perceived to be objective, the following paper argues that the contexts within which they are designed and employed play an important role in their functioning. The paper employs feminist theories of discrimination and oppression to show how seemingly objective technology can produce discriminatory consequences, particularly towards women and other marginalized groups.

Some of the sources of algorithmic biases include the presence of biased training data sets, the employment of proxies, and designs that resemble social stratification. In addition, it focuses on the limitations of traditional antidiscrimination approaches that often fail to adequately address cases of algorithmic bias because of their inability to address systematic and indirect forms of biases. The study considers the effectiveness of legal measures employed to counteract algorithmic discrimination and their ability to address questions of responsibility, accountability, and transparency by means of a comparative analysis of measures employed in the US, India, and the EU.

Ultimately, what the paper is able to show is that addressing algorithmic discrimination entails a lot more than just addressing technical concerns, and instead requires embracing a richer understanding of equality. In addition, the paper stresses that inclusion and participation must be at the center of decision-making processes in terms of developing policy and regulatory regimes, as well as taking steps to include feminism in AI governance.

Keywords: Algorithmic Bias, Feminist Legal Theory, Gender Justice, Artificial Intelligence, Structural Inequality, Intersectionality, AI Governance, Discrimination Law.

INTRODUCTION

The legal system has been trying to find the definition of equality for quite some time now. Discrimination does not always show itself explicitly, as the feminist movement has shown on many occasions. Sometimes it is so deeply rooted within our practices and systems that we consider them neutral and objective when, in reality, they can yield discriminatory results.[1]

At the moment, AI is often seen as a similar entity. AI is considered a tool that has no personal biases, opinions, or feelings. But it cannot exist without the data it was fed during training. The idea of its neutrality and objectivity seems quite questionable, considering that it may only reflect the current realities of our society.[2]

AI has become part of decision-making that affects people and does not operate within the technical arena anymore. It helps in policing, makes medical recommendations, assesses one's financial credibility, and filters job applications.[3] This technology is not socially independent. It exhibits social injustice rooted in gender because it is designed and trained by humans. As a result, the real possibility of such technology not only reproducing social injustice but also reinforcing it exists, especially in much larger scope.[4]

It should be noted that the issue of bias being hard to detect complicates the problem even further. Under normal circumstances, it is possible to challenge a decision if it seems biased. However, in the case of algorithms, the process can be obscure, making accountability difficult due to their opaque nature.[5] According to this research, technical progress alone is insufficient to address algorithmic bias. It is essential that the struggle for gender equality develops alongside the growing role of artificial intelligence. Ulitmately, the pursuit of fairness in artificial intelligence must remain aligned with broader commitments to social justice and equality.

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1. Catharine A. MacKinnon, *Reflections on Sex Equality Under Law*, 100 Yale L.J. 1281, 1285–86 (1991).
2. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 Calif. L. Rev. 671, 674–75 (2016).
3. Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 Geo. L.J. 1147, 1150–52 (2017).
4. Safiya Umoja Noble, *Algorithms of Oppression: How Search Engines Reinforce Racism* 1–3 (2018).
5. Frank Pasquale, *The Black Box Society: The Secret Algorithms That Control Money and Information* 3–7 (2015).

FEMINIST LEGAL THEORY AND STRUCTURAL INEQUALITY

The age-old idea that the law is fundamentally neutral, objective, and equally applicable to all members of society is questioned by feminist legal theory. According to feminist theorists, law is significantly shaped by social, political, and historical factors, most of which have been influenced by the patriarchal point of view, and is not just a body of unemotional rules. As such, there is a natural inclination for many laws to replicate existing power relations, even though on the surface they appear neutral. In other words, discrimination against women and other minorities could be disguised within neutral legislation.[6] Feminist legal theory is therefore more concerned with systemic inequalities found in institutions and actions, as opposed to individual instances of discrimination.

Differences in formal and substantive equality are among the fundamental principles of feminist legal theory. The former rests upon the obvious idea that like cases should be treated alike regardless of the specifics.[7] Even though such an approach helps to promote homogenization, it ignores the fact that people start from unequal positions in life. On the contrary, substantive equality realizes that sometimes equal treatment may lead to greater inequalities especially when structural oppression is already a part of people's lives. Instead, it strengthens the idea that at times people have to receive different treatment to achieve true equality. The essence of feminist critiques of those legal regimes that operate based on impartial laws while ignoring social reality is rooted in this discrepancy. At times, structural inequality operates not through obvious forms of discrimination but rather through normative understandings and assumptions. Even when the regulations seem fair, they may still reproduce inequality since those norms affect the interpretation of the law.[8]

A clear example of this can be seen in workplace expectations. Many professional environments are structured around the idea of uninterrupted career progression, constant availability, and limited caregiving responsibilities.

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6. Catharine A. MacKinnon, *Feminism, Marxism, Method, and the State: Toward Feminist Jurisprudence*, 8 Signs 635, 636–38 (1983).
7. Sandra Fredman, *Substantive Equality Revisited*, 14 Int'l J. Const. L. 712, 714–16 (2016).
8. Martha Albertson Fineman, *The Autonomy Myth: A Theory of Dependency* 8–10 (2004).

While these assumptions might seem to be rather neutral, for many women their real-life experiences resemble the stereotypically male pattern. For these reasons, individuals not adhering to this normative pattern – especially those assuming the caregiver role – might face structural disadvantage, which is rooted in the system and does not get recognized publicly.[9]

As a result, even without any explicit discrimination, people responsible for performing the care work, particularly women, face structural disadvantage. In some cases, what is neutral on paper may lead to inequality in practice.[10]

Furthermore, a deeper issue arises out of feminist legal theory which raises questions as to who gets their experience recognized in law. In previous generations, the experiences of those in power have determined what legal concepts such as "reasonableness" and "objectivity" are defined as. Consequently, women and other minorities could find their experiences less relevant or pertinent in legal matters. Ignoring alternative experiences that do not fit within the paradigm means the law could potentially promote inequality by failing to incorporate these views.[11]

Intersectionality is an important contribution made by feminist legal theory. Intersectionality recognizes that identities such as gender, race, class, caste, and sexuality do not operate independently from one another but have complex interrelationships with each other. Instead of facing discrimination on a singular front, individuals face multiple forms of discrimination.[12] Thus, a uniform policy for equality would be inadequate. The law has to look beyond generalizations and take into account the specific context in which discrimination occurs to tackle inequality.

In this regard, there might be a case where even the absence of any malicious intention could lead to structural inequality, especially for those individuals who take on caring responsibilities.[13]

9. Joan C. Williams, *Unbending Gender: Why Family and Work Conflict and What to Do About It* 1–4 (2000).
10. Joan C. Williams, *Reshaping the Work-Family Debate: Why Men and Class Matter* 19–21 (2010).
11. Martha Minow, *Making All the Difference: Inclusion, Exclusion, and American Law* 50–53 (1990).
12. Kimberlé Crenshaw, *Demarginalizing the Intersection of Race and Sex*, 1989 U. Chi. Legal F. 139, 140–42 (1989).
13. Martha Albertson Fineman, *The Neutered Mother, the Sexual Family and Other Twentieth Century Tragedies* 161–65 (1995).

The idea of intersectionality represents an important innovation in the study of law in feminism. This is because identity, whether in terms of gender, race, class, caste, or sexual orientation, is always connected in some way to other elements, and there are no singular entities. This means that discrimination is rarely experienced in isolation from other forms of discrimination but happens alongside each other, reinforcing and multiplying each other.[14] In this context, it is clear that lived experiences are much richer than can be explained through a generalized and one-dimensional notion of equality.

Furthermore, feminist legal theory shows that equality is a broader social goal that needs to be deliberately pursued rather than simply a legal principle.[15] It is not always enough to simply provide equality. To accomplish equality, it is important to take into account not only the outcomes but also the conditions under which they occur.[16.] This is especially important when taking into account systems based on historical data and social trends because they might unintentionally recreate the very discrimination that laws are designed to prevent.

When put together, however, feminist legal theory is able to provide an effective analytical tool with which to understand the process by which inequality can be built into legal systems in a manner that may not be obvious at first glance. The emphasis on intersectionality, substantive equality, and structural inequality enables this perspective to offer a much more sophisticated approach to determining what constitutes justice and equality. All of this is particularly important at this point in time, when the systems based on history and precedent are becoming increasingly influential.[17] Ultimately, however, this requires moving away from formal equality to substantive equality, this shift reflects a broader move in legal thought toward recognizing lived realities over abstract equality.[18] A world where laws help dismantle obstacles, create opportunities, and provide for justice for everyone in a meaningful sense. Both of these ideas emphasize the importance of laws that comprehend actual experiences and seek fairness.

14. Kimberlé Crenshaw, *Mapping the Margins: Intersectionality, Identity Politics, and Violence Against Women of Color*, 43 Stan. L. Rev. 1241, 1244–45 (1991).
15. Sandra Fredman, Discrimination Law 15–18 (2d ed. 2011).
16. Sandra Fredman, *Discrimination Law* 14–16 (2d ed. 2011).
17. Martha Albertson Fineman, *Equality, Autonomy, and the Vulnerable Subject in Law and Politics*, in *Vulnerability: Reflections on a New Ethical Foundation for Law and Politics* 13, 15–18 (Martha Albertson Fineman & Anna Grear eds., 2013).
18. Owen M. Fiss, *Groups and the Equal Protection Clause*, 5 Phil. & Pub. Aff. 107, 108–10 (1976).

UNDERSTANDING ALGORYTHMIC BIAS, MECHANISM AND MANIFESTATIONS

Whenever computer systems come up with outcomes that treat certain groups unjustly, then this is said to be algorithmic bias. While algorithms are often viewed as objective tools that simply process data, this may not be the case. This is because there is always some human influence in their development, purpose, and data sets used. In this case, algorithms cannot be seen as socially independent. The present day's institutions, history, and society influence these tools significantly. This means that social inequalities can be built into these automated systems and reproduced on an even larger scale through claims of objectivity.[19]

One of the most common causes of algorithmic discrimination is incomplete or biased data used for training purposes. Historical data plays a crucial role in identifying patterns and making decisions because it helps algorithms learn. Nonetheless, the algorithm will inherit any existing discrimination or biases found within the data, which will be replicated.[20] For example, when reviewing historical recruitment data, if there was an observable bias against hiring females for specific roles, the algorithm will interpret this as a prevalent pattern rather than discriminatory behavior. Eventually, the same discriminatory patterns could be reinforced, thus allowing past discrimination to subconsciously affect current decisions.

Bias can arise due to the choice of features and proxy variables being used. The algorithm can make use of other variables that will give off similar information despite the exclusion of sensitive variables such as gender from the data set. Variables such as location, education, occupation, and even purchasing behavior can be proxy variables for existing societal injustice.[21] The problem becomes hard to detect since the algorithm appears to make decisions purely based on unbiased data but ends up making decisions that affect specific groups of people.[22] Bias is then more hidden but still plays a role in decision-making.

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19. Solon Barocas, Moritz Hardt & Arvind Narayanan, *Fairness and Machine Learning: Limitations and Opportunities* 1–3 (2019).
20. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 Calif. L. Rev. 671, 677–80 (2016).
21. Latanya Sweeney, *Discrimination in Online Ad Delivery*, 11 Queue 10, 12–14 (2013).
22. Danielle Keats Citron & Frank Pasquale, The Scored Society: Due Process for Automated Predictions, 89 Wash. L. Rev. 1, 13–18 (2014)

It is also important to acknowledge that discrimination by design does not always emerge out of discriminatory intent. It arises out of the complex interplay of factors like data collection, design choices, and context in which the system operates. The system might operate on narrow definitions of success and imbalanced data, resulting in the emergence of bias even when there was no intent to discriminate on part of those who designed the system.[23]. This suggests that algorithmic discrimination is a much larger issue than merely being a technical one that can be solved in isolation. The solution to this problem involves considering the context in which such systems operate besides the programming.

Thus, algorithmic bias should be viewed as a socio-technological issue because it involves both human factors, patterns of historical inequality, and computations. The implications of such algorithmic bias become even more serious due to the increased use of artificial intelligence in spheres that control access to employment opportunities, finance, health care services, and other important resources.[24] In order to guarantee equal treatment in such situations, technological measures are clearly not enough. One also needs an appropriate approach to designing and deploying such systems along with ethical awareness and legal frameworks.[25]

CASE STUDY: GENDERED ALGORYTHMIC HARM

Algorithmic decision-making systems are now commonly used in hiring, where many see them as effective and unbiased tools. However, a well-known case involving Amazon shows how these systems can repeat and strengthen gender bias.[26] In 2018, Amazon created an AI recruitment tool meant to streamline the hiring process by reviewing resumes and ranking candidates.[27]

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23. Virginia Eubanks, *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor* 7–10 (2018).

24. Karen Yeung, *Algorithmic Regulation: A Critical Interrogation*, 12 Regul. & Governance 505, 507–10 (2018).

25. Karen Yeung, *Algorithmic Regulation: A Critical Interrogation*, 12 Regul. & Governance 505, 507–10 (2018).

26. Jeffrey Dastin, *Amazon scraps secret AI recruiting tool that showed bias against women*, Reuters (Oct. 10, 2018).

27. Ibid.

The system was trained on hiring data gathered over ten years. However, since the technology sector has been mainly male-dominated, the training data mostly included male applicants.[28]As a result, the algorithm learned to prefer resumes that looked like those of male candidates.[29]

Resumes featuring signs associated with women, such as attending women's colleges or using terms like "women's" in extracurricular activities, were penalized by the system.[30] The program used proxy indications that indirectly encoded gender, despite the fact that gender was not explicitly included as a variable.[31] This illustrates how structural disparities ingrained in past data can be sustained by ostensibly neutral processes.

This case demonstrates how discrimination can happen without deliberate bias from a feminist legal standpoint. Conventional anti-discrimination frameworks frequently depend on demonstrating overt or deliberate discrimination. But in this case, systemic tendencies in the data—rather than intentional human behavior—were the source of the bias.[32] This is consistent with the idea of disparate effect or indirect discrimination, in which results disproportionately harm a specific group even in the absence of overt discriminatory intent.[33]

The case also brings up significant issues with openness and accountability. Finding and fixing the bias became difficult because the algorithm's decision-making process was difficult to understand.[34] In the end, Amazon stopped using this technology after realizing its shortcomings.[35]

28. Ibid.

28. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 Calif. L. Rev. 671 (2016).

29. Jeffrey Dastin, Reuters, supra note 1.

30. Barocas & Selbst, supra note 4.

31. Sandra Wachter, Brent Mittelstadt & Chris Russell, *Why Fairness Cannot Be Automated*, 41 Oxford J. Legal Stud. 1 (2021).

32. Ibid.

33. Frank Pasquale, *The Black Box Society: The Secret Algorithms That Control Money and Information* (Harvard University Press, 2015).

34. Dastin, Reuters, supra note 1.

This case illustrates that algorithmic discrimination is not confined to a single domain but reflects broader societal inequalities. It also exposes the inadequacy of existing legal frameworks in addressing such forms of bias, as they are not well-equipped to deal with discrimination embedded within technical systems. A feminist legal approach, which emphasizes structural inequality and power dynamics, provides a more comprehensive framework for understanding and regulating such issues.

From a comparative legal perspective, this case also highlights how different jurisdictions respond to algorithmic discrimination. While the United States lacks a comprehensive federal framework specifically addressing algorithmic bias, the European Union has taken a more structured regulatory approach through instruments such as the General Data Protection Regulation and the proposed Artificial Intelligence Act. The GDPR provides individuals with certain rights related to automated decision-making, including the right to explanation and safeguards against decisions based solely on automated processing. Similarly, the AI Act adopts a risk-based approach, imposing stricter obligations on high-risk AI systems, including those used in employment. This demonstrates a more proactive attempt to address issues of transparency, accountability, and fairness in algorithmic systems, aligning more closely with feminist concerns about structural inequality.

REGULATORY RESPONSES AND COMPARATIVE ANALYSIS

Indeed, all legal systems across the globe have begun taking steps to address increasing fears of bias in algorithms by developing legislative frameworks designed to foster accountability, transparency, and fairness in the use of AI.[36] While their form and implementation may differ, these frameworks reflect a better appreciation for the risks that these decision-making machines may present, particularly regarding discriminatory and unequal structures.[37]

One of the finest approaches towards regulating AI that the EU has undertaken is the formulation of its Artificial Intelligence Act. The EU Commission has developed a risk-based approach to regulating AI through this act, where it identifies levels of risks that different kinds of AI pose on human beings and society.[38]

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35. Washington v. Davis, 426 U.S. 229, 239–42 (1976).

36. Griggs v. Duke Power Co., 401 U.S. 424, 431–32 (1971).

37. Sandra Wachter, Brent Mittelstadt & Chris Russell, Why Fairness Cannot Be Automated: Bridging the Gap Between EU Non-Discrimination Law and AI, 41 Comput. L. & Sec. Rev. 105567 (2021).

This approach subject's organizations which can be said to cause a high risk for fundamental rights to higher regulatory oversight in areas like employment and public safety among others. The rationale behind this policy is a move to achieve a balance between safeguarding people from harms and promoting innovations.

For high-risk systems like those used in credit scoring, hiring processes, and law enforcement, there will be stricter regulations regarding this system. These will involve regulations regarding data quality and governance, higher transparency during decision making, human supervision processes, and compliance testing before deploying these kinds of systems.[39] The reason for these regulations is to ensure the proper functionality of the technology.

Such an approach is particularly relevant given the recognition that there might be bias at the design level itself. The concept is premised on the idea of preventing damage from occurring in the first place instead of treating it once it does happen. It seeks to avoid the risks of discrimination and unfairness before they are entrenched in the processes, through the application of these measures from the very beginning of the development of AI systems.[40] Besides the laws, many international institutions have also influenced discussions on responsible AI globally. For instance, the Organization for Economic Cooperation and Development (OECD) has come up with its own AI Principles that highlight accountability, robustness, transparency, inclusive growth, and human-centric values.[41]

In a similar way, the UNESCO Recommendation Concerning the Ethics of Artificial Intelligence highlights the need for ensuring gender equality, fairness, and non-discrimination within the process of developing and utilizing AI technologies. In sum, these frameworks demonstrate the emergence of a growing international consensus about the importance of considering ethical considerations when working with AI technology, especially when there is a risk of increasing structural inequality in some cases. As opposed to the international legal frameworks, the regulatory system in the US operates within sectors. It regulates artificial intelligence through various anti-discrimination laws and agency guidance in the absence of a unified national framework.[42]

38. OECD, Recommendation of the Council on Artificial Intelligence, OECD/LEGAL/0449 (2019).

39. UNESCO, Recommendation on the Ethics of Artificial Intelligence (2021).

40. Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act), COM (2021) 206 final (Apr. 21, 2021).

41. *Id.* arts. 6–7.

Algorithmic systems in the United States that produce discriminatory outcomes can be held accountable within the current laws, including consumer protection laws and anti-discrimination laws.[43] But due to the absence of a single set of laws at the federal level that specifically regulate AI, a fragmented system has emerged, whereby self-regulation within the industry is heavily practiced, and each case of discrimination or harm caused by algorithmic technologies is dealt with individually.[44] This can make it difficult to ensure consistency in how such harms are addressed.

As per the current scenario, the regulatory framework in India is still in its nascent stage. At the moment, no particular legislation exists that regulates artificial intelligence. While stressing on the need for responsible and inclusive use of artificial intelligence, policy documents such as the National Strategy for Artificial Intelligence largely focus on innovation and capacity building rather than legal obligations.[45] Yet, the potential existence of a legal framework in the case of algorithmic discrimination is found in the provisions of the constitution, primarily Article 14.[46] The issue with implementing such broad constitutional protections in the realm of algorithms lies in the fact that the law is yet to develop in this area.

From a comparison of these models, it becomes clear that there are variations on how various governments find the delicate balance between innovation and regulation. Due to its focus on security and accountability, the EU model is characterized as being more conservative and more rights-oriented.[47] The US model, for instance, still focuses more on market-based processes and existing legislation despite these variations. The Indian model is more in the process of transitioning by blending principles of the constitution with policymaking.
Irrespective of the differences in the models, all governments agree that accountability, transparency, and justice should be ensured for algorithms.

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42. Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act), arts. 8–15, COM (2021) 206 final (Apr. 21, 2021).

43. Sandra Wachter, Brent Mittelstadt & Luciano Floridi, Transparent, Explainable, and Accountable AI for Robotics, 2 Sci. Robotics eaat7651 (2017).

44. OECD, Recommendation of the Council on Artificial Intelligence, OECD/LEGAL/0449 (2019); UNESCO, Recommendation on the Ethics of Artificial Intelligence (2021).

45. .U.S. Equal Emp. Opportunity Comm'n, Artificial Intelligence and Algorithmic Fairness Initiative (2021); Federal Trade Comm'n, Aiming for Truth, Fairness, and Equity in Your Company's Use of AI (2021).
46. Federal Trade Comm'n, Big Data: A Tool for Inclusion or Exclusion? (2016); *see also* 15 U.S.C. §§ 41–58 (Federal Trade Commission Act).

What is also significant is the fact that many of the regulatory efforts that have been put forward tend to tackle problems that have an intrinsic link to the feminist jurisprudence of equality and structural inequality.[48] Both of these perspectives are characterized by the fact that they value accountability, equity, and non-discrimination. Implicitly, these perspectives acknowledge that even when a system appears neutral on paper, there will still be discriminatory results from such a system.[49] It is vital for any legislative approach to adapt in order to consider technological, as well as other, forms of prejudice.

REIMAGINING GENDER JUSTICE. A FEMINIST HOMEWORK FOR AI GOVERNANCE

As artificial intelligence begins to make its way into the field of decision-making, there is an implicit shift in how questions about justice are being raised and how they are being resolved. These tools, which seem to be impartial, efficient, and technologically advanced, become involved in resolving cases where human agents were traditionally involved. But such impartiality does not necessarily ensure fairness.[50] As algorithmic decision-making systems begin to govern more feminist legal theory has been pointing out for decades that inequality often lies at the very heart of the institution.

In line with this theory, formal mechanisms of equality fall short when it comes to ensuring equality between genders.[51] The primary concern for past legal measures was to prohibit discrimination directly, yet algorithmic technologies bring to light the limitations of such an approach. Even if no direct intention to discriminate prevails, activities based on data which is already prejudiced will inevitably reproduce similar bias, without having any malicious intent.[52] Such a situation complicates the obligations of states. It is not enough anymore to have neutral legislation, since the implementation process of the system also matters. This also underscores the need for states to adopt a more substantive approach to equality, one that actively addresses structural disadvantages rather than merely prohibiting overt discrimination.

48. U.S. Equal Emp. Opportunity Comm'n, Artificial Intelligence and Algorithmic Fairness Initiative (2021).
49. NITI Aayog, National Strategy for Artificial Intelligence #AIforAll (2018).
50. India Const. art. 14.
51. Proposal for a Regulation of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act), COM (2021) 206 final (Apr. 21, 2021).
52. Catharine A. MacKinnon, *Sex Equality* (2007).

Hence, it becomes essential to have a re-evaluation of the way governments regulate in order to think about gender justice in a new manner. The need for regulatory frameworks that will anticipate problems of gender inequality and address them even before any injustice occurs is growing day by day.[53] It requires setting clear guidelines for data gathering, training models, and outcome assessment. Methods of ensuring equity, accountability, and transparency cannot just be technical measures but are necessary for making sure that technological systems are ethically aligned with equality.

Nevertheless, the voices of those who have the greatest stake in artificial intelligence cannot be separated from gender justice within the present-day context. For many years now, feminist theory has rejected the idea that there is such a thing as a standpoint that will represent everybody and has highlighted the importance of lived experiences.[54] Consequently, we should involve even more parties when making policy regarding artificial intelligence. This way, we could make sure that the process of designing and supervising such a system would reflect various different realities and would not rely on assumptions alone.

Transparency is yet another key element of the aforementioned reinvention. The ability of individuals to truly understand the process through which decisions of automated systems are reached is essential. Without such transparency, it becomes difficult to hold these systems accountable and also raises barriers to contesting unfavourable results.[55] It is for this reason that transparency is directly tied to access and agency in that it facilitates challenge and helps to build trust in systems that exert increasing influence on individuals' lives. Finally, an intersectional approach is required for understanding gender justice.

Gender alone is not the sole factor determining inequality, and other factors come into play as well.[56] Such an analysis that treats gender as a monolith could very well ignore such differences and fail to account for the differences through which various groups experience interactions within algorithmic systems.

53. Kimberlé Crenshaw, Demarginalizing the Intersection of Race and Sex, 1989 U. Chi. Legal F. 139.

54. Cathy O'Neil, *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (2016).

55. Sandra Fredman, *Discrimination Law* 21–35 (2d ed. 2011).

56. Solon Barocas & Andrew D. Selbst, Big Data's Disparate Impact, 104 Calif. L. Rev. 671 (2016).

To ensure that actions against inequality are reflective of such lived realities as opposed to blanket statements, there is a need for a more nuanced analysis, whereby the government should account for such intersections when developing and implementing policy measures.[57]

Through this process, revising the concept of gender justice has less to do with creating novel ideas than with the implementation of existing ideas of equality in the rapidly changing field of technology.[58] This calls for a reassessment by governments regarding how decisions are made, how the system functions, and how responsibility is effectively managed. Herein lies the dilemma that is fundamentally normative and structural rather than technological. Law, policy, and technology have to work together in order to ensure that progress in one sphere does not end up replicating injustices in another.

CONCLUSION FROM BIAS MITIGATION TO STRUCTURAL TRANSFORMATION

Various technical means, such as the application of fairness measures, changes to models, and even post hoc adjustments, have often been the center of attempts to solve the issue of algorithmic bias.[59] While all of these approaches may be quite helpful in overcoming bias, they tend to work within an existing framework rather than questioning its underlying assumptions. As a result, the problem of bias often tends to be regarded as purely technological, as well as requiring some type of fixing on a technological level. Such an understanding of the issue is fundamentally altered by the feminist legal perspective.[60] However, a feminist legal perspective shifts the focus from merely correcting outcomes to interrogating the power structures and social conditions that shape those outcomes in the first place.

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57. OECD, Recommendation of the Council on Artificial Intelligence, OECD/LEGAL/0449 (2019); UNESCO, Recommendation on the Ethics of Artificial Intelligence (2021).

58. Patricia Hill Collins, *Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment* (2d ed. 2000).

59. Frank Pasquale, *The Black Box Society: The Secret Algorithms That Control Money and Information* (2015).

60. Kimberlé Crenshaw, Mapping the Margins: Intersectionality, Identity Politics, and Violence Against Women of Color, 43 Stan. L. Rev. 1241 (1991).

From this perspective, the reduction of bias would only be the first step, as it does not fully account for the conditions responsible for causing the observed differences, despite its role in helping reduce them.[61] In order for there to be any real change, it is important to take into consideration more broad-based structural concerns, including the workings of institutions, how information is collected, and why certain decisions are made. This involves questioning whether the assumptions embedded in technology reflect principles of equality or simply perpetuate existing tendencies.

This means that there should be a more proactive and forward-looking approach adopted by the governments. The regulatory process will have to affect the environment in which the algorithmic systems are being created and utilized; it will not be confined only to overseeing them.[62] It will involve ensuring that such values as justice, accountability, and inclusivity are embedded within the systems themselves and not merely dealt with once problems occur. However, continuous evaluation is essential since the social environment and technology itself are dynamic and lead to new forms of discrimination becoming apparent.

From a basic standpoint, a higher understanding of the problem itself lies in the shift from addressing biases to transforming the structure. For technology such as artificial intelligence, achieving gender equity cannot be done with piecemeal solutions or superficial changes. Instead, there needs to be a larger approach that ties in technology, politics, and laws into an actual pursuit of equality.[63] From the lens of feminist legal theory, this approach is justified as equality means solving the problems that cause inequality in the first place.

Ultimately, taking into account gender justice in algorithms means developing a system that is genuinely just in the long term rather than merely reducing biases. It will require a deeper examination of the institutional agenda, higher involvement in the process of decision making, and a more effective system of accountability that can address any form of inequality whether explicit or implicit.[64] In this way, it would be possible to ensure that technology development does not come at the expense of justice.

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61. Kimberlé Crenshaw, Mapping the Margins: Intersectionality, Identity Politics, and Violence Against Women of Color, 43 Stan. L. Rev. 1241 (1991).

62. Sandra Fredman, *Discrimination Law* (2d ed. 2011).

63. Solon Barocas, Moritz Hardt & Arvind Narayanan, *Fairness and Machine Learning: Limitations and Opportunities* (2019).

64. Catharine A. MacKinnon, *Sex Equality* (2007).

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