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# Bias in AI Systems and Its Impact on Deprived Groups

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**Abstract**

Artificial Intelligence (AI) is now used to make decisions in many areas such as jobs, healthcare, education, banking, policymaking, and government welfare schemes. Although people often believe AI is neutral and objective, these systems can actually repeat and worsen the social inequalities persistently prevailing in society. This paper explains how AI bias harms deprived and marginalised groups such as Dalits, Adivasis, religious minorities, women, people with disabilities. AI becomes biased when the data used to train it is incomplete, unequal, or influenced by stereotypes. Problems also arise when algorithms are designed in ways that favour dominant social groups. This leads to real-world consequences; hiring software may reject applicants based on caste-related names or rural backgrounds; predictive policing systems may unfairly target communities that are already vulnerable.

These issues increase social exclusion by limiting access to essential opportunities and services. The paper trying to argues that reducing AI bias is not only a technical challenge but also a social responsibility. It calls for more inclusive datasets, transparent algorithms, regular bias checks, involvement of affected communities in AI design, and strong regulations. Ensuring fairness and accountability in AI is necessary to prevent digital discrimination and protect the constitutional promise of equality for all as well as establish constitutionalism.

## Introduction

Artificial Intelligence (AI) is now used in many important areas like jobs, policing, education, banking, healthcare, and government welfare schemes. People often think that AI is fair and neutral because it works with data. But many studies show that AI can repeat and even increase the inequalities already present in society. AI becomes biased when the data used to train it contains discrimination, stereotypes, or missing information about certain communities. When the data itself is unequal, the AI system also becomes unequal. This bias affects deprived and marginalized groups the most such as Dalits, Adivasis, religious minorities, women, people with disabilities, LGBTQ+ communities, and poor families. AI based tools like job selection software, loan approval systems, facial recognition, or predictive policing can treat these groups unfairly. They may be wrongly classified, denied important services, or exposed to extra surveillance. The problem becomes more serious because AI decisions are usually hidden and difficult for common people to understand or question.

AI bias also increases digital inequality. Many rural, excommunicated, or socially excluded communities have low digital literacy, weak internet access, and less online presence. Because of this, they are not properly represented in the data, so AI systems fail to understand them correctly. Bias becomes even

stronger when caste, gender, class, and location come together. For example, facial recognition often works poorly for darker skin tones, hiring tools may penalize women for taking career breaks, and credit scoring systems may call penury people "high risk" simply because they were historically excluded from society or mainstream. Therefore, AI bias is not just a technical problem; it is a social problem with serious effects on equality, justice, and human rights. It is important to understand how AI becomes biased, who suffers the most, and how these problems can be reduced. I am trying to discuss over here the causes of AI bias and its harmful impact on deprived groups, and argues that without strong reforms, AI may increase the same inequalities it promises to reduce.

**History of Discrimination:**

In India, discrimination has developed slowly over thousands of years because of social rules, religious beliefs, and political power. It appears in many forms, such as caste discrimination, inequality between men and women, untouchability, exclusion on the certain caste based, problems faced by tribal communities, and differences between purity and impurity. The caste system has been one of the most defining and enduring structures of Indian society, shaping social relations, economic opportunities, and political life for centuries. It divides people into hierarchical groups based on birth, placing Brahmins at the top and Shudras and Dalits at the bottom. This hierarchy has historically legitimized and preserved unequal access to resources, privileges, and rights. As Louis Dumont observed that, "caste operates through an ideology of purity and pollution that regulates social distance, occupation, and everyday interactions[1]."

1. **Discrimination Against Lower Castes**: Dalits, formerly known as "Untouchables," have faced the harshest forms of exclusion. They were traditionally denied entry into temples, access to wells, educational institutions, and even public roads. B.R. Ambedkar emphasizes that "caste is not merely a division of labor, but a division of laborers that sanctions inequality as a religious duty[2]." Even after legal abolition of untouchability through Article 17 of the Indian Constitution, discrimination continues in subtle and overt forms such as social boycotts, segregated settlements, caste-based violence, and exclusion from decision-making bodies.

2. **Educational and Economic Discrimination**: Caste based discrimination also shapes access to education and economic resources. Dalits and Adivasis experience lower literacy rates, unequal school enrolment, and higher dropout rates due to social stigma and economic hardship. Thorat and Newman's study on job discrimination demonstrates that applicants from Dalit and Muslim communities are less likely to receive interview calls compared to upper caste candidates despite having identical qualifications[3].This structural disadvantage limits upward mobility and reproduces long-term poverty.

3. **Gender and Caste Discrimination**: Caste and gender intersect to produce even deeper inequality for women from marginalized castes. Dalit women often face triple discrimination on the basis of caste, gender, and class. They are disproportionately affected by sexual violence, exclusion from community resources, and hazardous forms of labor. According to Gopal Guru, "Dalit women's experiences cannot be fully understood without recognizing how caste and patriarchy jointly operate[4]."

4. **Contemporary Forms of Caste Discrimination**: Although modern India has seen significant social reforms, urbanization, and affirmative action policies, caste based discrimination persists in new forms. Studies show that residential segregation, discrimination in dining spaces, and caste based hatred on social media remain widespread. "Even digital platforms and AI systems are found to reflect caste bias due to existing inequalities in data representation[5]". This shows that caste adapts to new social environments and technologies rather than disappearing.

Caste based discrimination continues to shape social inequality and restrict equal citizenship in India. Despite constitutional protections and social justice movements, caste remains embedded in social relations, institutions, and cultural practices. Addressing caste discrimination requires both legal enforcement and social transformation to challenge deeply rooted hierarchies.

Religious scriptures provide legitimate base for the discrimination such as Rigveda, Manusmriti, etc.

*"The Brahmin was his mouth, the Kshatriya from his arms,*
*the Vaishya from his thighs, and the Shudra from his feet."*

The verse describes the cosmic being, Purusha**,** whose body is symbolically divided into four parts, each corresponding to a varna: the *Brahmin* emerges from his mouth, the *Kshatriya* from his arms, the *Vaishya* from his thighs, and the *Shudra* from his feet. In later centuries, this imagery was used to assign social status and roles Brahmins as priests and teachers, Kshatriyas as warriors, Vaishyas as traders, and Shudras as servants and laborers. Scholars argue

that the symbolism reflects an attempt to create a divine origin for social stratification by linking human society with cosmic order.[6]

"शूद्रो धनं समाश्रित्य स्वामिकर्माणि सेवते ।
ततस्तस्य धनं सर्वं स्वामिनः स्याद् न्यायतस्मृतम् ॥ :[7]"

"If a Shudra, through wealth gained by serving his masters, becomes proud of his riches, then all that wealth rightfully belongs to his master."

**Literature Review**

1) **Crawford (2016):** highlights that algorithmic bias is often rooted in the data used to train AI systems, which reflect historical, cultural, and social prejudices

2) **Barocas and Selbst (2016):** contend that seemingly neutral technical tools can produce discriminatory outcomes because they encode societal biases, particularly against marginalised groups.

3) (**Khera, 2019; Iyer & Iyer, 2020):** These errors often result in the denial of essential services, demonstrating how algorithmic bias intersects with caste, class, gender, and geography.

4) **Buolamwini and Gebru (2018):** found that facial recognition systems misidentify darker-skinned women at significantly higher rates than lighter-skinned men, illustrating how AI systems can perpetuate racial and gender hierarchies

The image looks like a multi layered digital society. At the top, a small group controls data and decisions. In the middle layers, people work on screens and run systems. At the bottom, a large crowd seems trapped in repetitive or forced tasks, with some of them even holding chains or broken devices. Everything is connected by glowing wires that flow upward, as if power and information only move one way. The picture is a strong metaphor for what happens when power, knowledge, and opportunity flow only upward and never downward. Connecting it to a caste like hierarchy highlights the dangers of any society where birth decides destiny.

This image clearly represents what Dr. B.R. Ambedkar repeatedly argued "caste is not just a social system it is a system of graded inequality that arranges people from top to bottom, giving dignity to a few and oppression to many[8]". The pyramid like structure in the image mirrors exactly this logic. At the very top, a small group controls all advanced technology, information, and decision making. This is the modern version of the "upper caste monopoly over knowledge and power." Ambedkar said that "caste survives by controlling access to education, technology, and public life[9]". The topmost figures in the image symbolise those who benefit from this monopoly.

The middle layers show workers who have partial access to computers and digital tools but remain under constant surveillance. This reflects caste offers limited mobility to some groups, but only within boundaries set by the dominant castes. These workers are useful to the system

but never equal. They follow rules decided by those above them, similar to how caste society allows some communities conditional status but denies them true power or independence. The image makes it clear that even in the digital world, control flows from top to bottom, not democratically, but hierarchically.

The bottom layer exposes the harshest truth the entire structure rests on the labour of those who remain invisible, undervalued, and exploited. The crowded, dimly lit space full of workers doing basic or manual tasks strongly resembles the historical situation of Dalits, Adivasis, and other oppressed communities. Dr. Babasaheb Ambedkar argued that caste forces certain groups into degrading labour and then denies them dignity for doing that labour. The image visualises this injustice the lowest groups keep the system running, yet they receive no recognition, rights, or opportunity. The image is not just a futuristic scene it is a powerful warning. It shows that if caste values continue, even modern technology will reproduce old hierarchies. Ambedkar insisted that social equality must come before technological progress; otherwise, new systems will simply become new forms of the same old oppression[10]. This digital pyramid proves his argument: unless caste is destroyed at its roots, it will rebuild itself in every new space in workplaces, in cities, and even in digital networks.

**Challenges of Bias in AI Systems and Their Impact on Deprived Groups**

- **Data Inequality:** Data inequality is a major reason why AI systems become biased. AI learns from past data, so if the data is incomplete or imbalanced, its decisions will also be unfair. When groups like Dalits, Adivasis, religious minorities, women, LGBTQ+ people, and persons with disabilities are not properly represented in datasets, the AI gets an incomplete picture of society. It then learns patterns that favour powerful or majority groups and ignores the experiences of marginalised communities. This results in wrong predictions, unfair decisions, and discrimination. In this way, data inequality strengthens existing social inequalities and increases digital exclusion instead of reducing it.
- **Historical and Social Bias Embedded in Data :**Historical and social bias embedded in data is another major cause of unfair outcomes in AI systems. Indian society has long been shaped by caste hierarchy, patriarchy, and class inequality, and these biases often get recorded in historical documents, official records, and online data. When AI models learn from such biased information, they unintentionally absorb and repeat the same discriminatory patterns. As a result, modern digital systems end up reinforcing old social inequalities instead of challenging them. For example, a job recruitment AI might favour applicants with upper caste surnames or give preference to male candidates because the data it was trained on reflects past hiring biases. This shows how historical injustice gets carried forward into AI based decision making. When I performed this test, the result was shocking for me. When I asked the prompt “Generate an image of a twenty first century upper-caste couple,” the result was the first image. But when I repeated the prompt and replaced “upper caste” with “lower caste,” I received the second image.

The two images show different ways in which caste, class, and social position are represented visually in Indian society and media. Even though we cannot tell a person's caste just by looking at them, the way the images are composed the clothing, the setting, and the surroundings acts as symbols that reflect long standing ideas about social hierarchy. Dr. Babasaheb Ambedkar repeatedly argued that, "Caste survives by attaching social meaning to objects like clothing, housing, posture, and environment.[11]" Although the photographs feature surreal individuals whose actual caste identity cannot be identify visually, the compositional elements, clothing, and spatial context in each image work as symbolic markers that align with historically settled caste class imaginaries. In the first image, the couple is positioned within an environment that suggests relative equipped with facility smooth pathways, greenery, and an orderly setting elements that visually evoke middle class stability and socio economic security. Their attire reinforces this semi urban, aspirational aesthetic the man's tucked formal shirt, clean shave, and composed posture, along with the woman in a sari with a refined drape, minimal accessories, and a confident facial expression, collectively we can said they are associated with educated, salaried, and upwardly mobile social groups. In Indian representational culture, such traits are frequently linked to dominant caste identity, demonstrating how everyday visual cues become representative of structural privilege.

By contrast, the second image draws upon a different repertoire of signs to construct a representation aligned with rural and socio-economically marginalised contexts. The background featuring unplastered walls, tin-roofed structures, and an uneven path situates the subjects within a rural built environment marked by infrastructural precarity. The clothing similarly encodes traditional cultural norms often associated with agrarian or labouring communities: the woman's sari is brightly coloured, draped in a rural style, and worn with the pallu covering the head a practice linked to conservative gender norms and community traditions in many caste marginalised rural regions. The man's untucked shirt, simpler grooming, and restrained body language further contribute to the representation of limited economic resources and traditional social positioning. While both couples share a similar medium brown complexion demonstrating that skin colour is not a reliable indicator of caste the symbolic deployment of clothing, posture, and spatial setting produces a clear visual contrast between the two images. Taken together, the images do not reveal actual caste identity but instead demonstrate how visual culture operates through a set of encoded signs that audiences routinely interpret as indicators of caste and class stratification.

- **Bias in automated decision-making in public services**: It creates serious problems for marginalised groups. Many government systems such as welfare delivery, Aadhaar-based authentication, facial recognition, and predictive policing use AI tools that can sometimes make mistakes. Because these technologies are often trained on incomplete or biased data, they may fail more often for Dalits, Adivasis, religious minorities, and people living in poverty, who rely heavily on public services. For example, Aadhaar fingerprint mismatches have been reported more frequently among manual labourers and older adults, causing denial of rations or pensions[11]. "Studies on facial recognition also show that error rates are higher for darker skinned individuals and women[12]". These mistakes end up harming communities that already face discrimination, making access to essential government services even more difficult.
- Cultural and linguistic bias in AI systems arises because most models are trained mainly on widely used languages such as English and Hindi, while tribal languages, regional dialects, and mixed code speech receive very little representation. "This creates barriers for linguistic minorities, who may experience frequent errors, misinterpretations, or exclusion from digital services". Scholars such as Joshi et al. note that many Indian languages are classified as "low resource," meaning they lack sufficient digital data for AI training[13]. Similarly, Bird argues that the neglect of Indigenous and minority languages in computational tools reinforces existing cultural inequalities[14]. Such linguistic bias limits access to information, reduces participation in digital platforms, and deepens the marginalisation of minority language communities.

**Research Methodology and Theory:**

This research uses a mixed methods research design to examine how bias in AI systems affects deprived groups, combining qualitative insights with quantitative model analysis to capture both the technical and social dimensions of the problem. Qualitative data will be analysed through thematic analysis and critical discourse analysis, using an Ambedkarite lens to understand structural inequality and caste, class, power embedded in digital systems. Along with this mixed methods research design, the study also incorporates a semiotic research methodology to analyse the quixotic frame of

pictures associated with AI systems and their representation of deprived groups. Semiotic analysis enables the decoding of signs, symbols, colours, gestures, spatial arrangements, and visual metaphors embedded in images that portray caste, class, and technological power.

**Conclusion**

This study shows that bias in AI systems is not accidental or purely technical; it reflects deep social hierarchies that are reproduced through skewed datasets, uncritical design, and opaque decision making. Marginalised communities such as Dalits, Adivasis, women, linguistic minorities, persons with disabilities, and the poor face higher rates of exclusion, misrecognition, and surveillance harms when interacting with AI. The lack of transparency in government and corporate AI systems prevents meaningful public scrutiny. Technical audits show that facial recognition misidentifies darker-skinned people more often, speech systems fail for tribal languages, and biometric authentication often excludes manual labourers and the elderly. When I think about this problem profoundly, I perceive these challenges as a student of Humanities or Social Sciences.

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