Scholarly Research Journal for Humanity Science & English Language,
Online ISSN 2348-3083, SJ IMPACT FACTOR 2024: 8.058,
https://www.srjis.com/issues_data/240
PEER REVIEWED, REFEREED & INDEXED JOURNAL, OCT-NOV 2024, VOL-12/66

UNVEILING GENDER BIAS IN AI: ETHICAL CHALLENGES AND GLOBAL FAIRNESS WITH INSIGHTS FROM JHARKHAND, INDIA

Dr. Annita Ranjan

Assistant Professor, Department of Psychology

Gossner College, University of Ranchi, Ranchi. Jharkhand

Paper Received On: 21 October 2024

Peer Reviewed On: 25 November 2024

Published On: 01 December 2024

Abstract

Artificial Intelligence (AI) is transforming industries globally by enhancing efficiency and enabling data-driven decisions. However, its widespread adoption has surfaced significant ethical issues, notably gender bias within algorithmic systems. This study investigates the ethical dilemmas of AI in perpetuating or reducing gender bias across key sectors such as employment, healthcare, and financial services. While international research underscores AI-induced gender disparities, there is limited understanding of its localized effects, particularly in regions like Jharkhand, India. To address this, the research conducts a comparative analysis of global trends and localized data from Jharkhand, incorporating primary data from the region and secondary data from Meghalaya and the broader North East of India. Findings indicate that AI-driven recruitment, healthcare algorithms, and credit-scoring systems disproportionately disadvantage women, mirroring global trends and highlighting region-specific challenges influenced by cultural, social, and economic factors. The study emphasizes the unique obstacles women in Jharkhand face, including restricted access to AI opportunities, and provides an ethical critique of algorithmic decision-making that may exacerbate existing inequalities. It proposes solutions such as developing inclusive AI systems, implementing regulatory oversight, and establishing ethical frameworks focused on fairness, accountability, and transparency. Ultimately, this research offers actionable recommendations to mitigate AI-induced gender bias, advocating for inclusive datasets, regular bias audits, and AI literacy programs to empower women in underrepresented areas like Jharkhand, thereby contributing to the broader discourse on ethical AI deployment.

Keywords*: Artificial Intelligence (AI), Gender Bias, Ethical Frameworks, AI in Employment and Finance, Culturally Sensitive AI Deployment.*

Introduction

Artificial Intelligence (AI): Ethical Challenges of Gender Bias

AI is revolutionizing sectors such as healthcare, finance, and recruitment by improving efficiency and decision-making. However, ethical concerns have emerged regarding AI's potential to perpetuate gender bias. Trained on historical data, AI systems often replicate and amplify existing societal inequalities. As O'Neil (2016) argues in *Weapons of Math Destruction*, biased algorithms can produce discriminatory outcomes, disproportionately affecting women's access to employment, healthcare, and financial services (Buolamwini & Gebru, 2018).

Global studies highlight how AI-driven recruitment tools disadvantage women, particularly in male-dominated fields, while healthcare algorithms often yield less accurate results for women, especially minorities (World Economic Forum, 2020). Despite global discourse, the localized impact of AI-induced gender bias remains underexplored, particularly in regions like Jharkhand, India.

This study examines the ethical challenges of AI in perpetuating gender bias in Jharkhand, focusing on recruitment, healthcare, and financial inclusion. It integrates primary data from women in Jharkhand and comparative insights from Meghalaya to analyze AI's interplay with regional socio-cultural norms.

The objectives are to:

1. Compare global and local patterns of gender bias in AI systems.
2. Explore challenges women face due to AI in Jharkhand's socio-economic context.
3. Propose solutions for ethical AI systems, such as regulatory reforms, diverse datasets, and AI literacy programs.

By bridging global insights and regional analysis, the research aims to foster fair, transparent, and inclusive AI systems that mitigate gender bias, ensuring equitable opportunities for women in Jharkhand and beyond.

Literature Review

Global research reveals that AI systems often replicate and amplify societal biases, disadvantaging women and marginalized groups. Cathy O'Neil (2016) in *Weapons of Math Destruction* demonstrated how biased historical data causes AI algorithms to reinforce exclusionary practices in employment, education, and credit scoring. Buolamwini and Gebru (2018) highlighted racial and gender biases in facial recognition technologies, which performed poorly for darker-skinned women, raising ethical concerns in law enforcement and hiring. Similarly, the World Economic Forum (2020) reported that AI-driven hiring tools often reinforce gender stereotypes, worsening underrepresentation in male-dominated fields like technology and finance.

In India, **NITI Aayog (2018)** recognized the risks of AI systems exacerbating existing hierarchies, especially disadvantaging women in recruitment and financial services. However, research largely focuses on urban contexts, neglecting rural areas where socio-economic barriers are pronounced. This study addresses the gap by exploring how AI-driven systems in healthcare, recruitment, and financial services impact women in Jharkhand.

Additionally, a comparative analysis examines AI's impact on gender in Meghalaya, a matrilineal society, versus patriarchal Jharkhand. Meghalaya's cultural context, where inheritance and lineage pass through women, presents a unique lens to study AI's interaction with gender dynamics.

Initiatives like the **Digital Northeast Vision 2022** introduce AI in governance, agriculture, and healthcare across North East India, but their gendered impact remains underexplored. This research contributes critical insights into how AI systems perpetuate or mitigate gender bias, offering a nuanced understanding of socio-cultural influences in India.

Methodology

Research Design

This study adopts a **mixed-methods approach**, integrating **primary data collection** from **Jharkhand** with **secondary data** derived from **global sources** and the **North East of India**, particularly **Meghalaya**. In addition to This methodological design ensures a **comprehensive analysis** of AI-induced gender bias by combining the richness of qualitative insights with the empirical rigor of quantitative data. The **primary focus** of the research is on understanding the extent to which **AI systems perpetuate or mitigate gender bias** in sectors where AI technologies have already been implemented, such as **recruitment** and **financial services**.

This dual approach allows the study to juxtapose **global trends** with **localized findings** from Jharkhand, providing a **comparative perspective** that captures the **cultural, social, and economic specificities** of the region. Furthermore, the study incorporates secondary data from the **North Eastern states**, particularly **Meghalaya**, which presents a **unique socio-cultural environment** due to its **matrilineal structure**. By adopting this design, the research aims to uncover the **differential impact** of AI systems on **gender dynamics**, both globally and locally.

A. Sampling Breakdown Table

The following table shows the number of women taken from each category during sample study.

Table 1: Women sampled from each category

Participant Category	Number of Participants
Women Job Seekers (AI-driven Recruitment)	49
Women Entrepreneurs (AI-based Financial Systems)	51
Employees (AI-driven Hiring Systems)	50
Total Participants	**150**

B. Access to AI-Based Employment and Financial Platforms by Education Level

The following table shows how different education levels influence women's access to AI-based recruitment platforms and financial services in Jharkhand.

Table: 2: Access to AI-Based Employment and Financial Platforms by Education Level

Education Level	Access to AI-Based Employment Platforms	Access to AI-Based Financial Platforms
Below Secondary	34.2%	29.5%
Secondary Education	41.8%	38.7%
Graduate	58.3%	50.9%
Postgraduate	65.9%	60.2%

1. **Data Collection Methods**:

   The primary data collection involved two main methods:

   - **Surveys**:

     The survey instrument collected **quantitative data** from participants regarding their interactions with AI-driven systems in the **employment** and **financial sectors**. The survey included questions designed to assess participants' **perceptions of fairness**, their **experiences with AI tools**, and the **outcomes** of those interactions. Specific metrics was included whether participants believe AI-driven systems are biased in their favour or against them, the transparency of the decision-making process, and the overall impact on their **employment** and **financial opportunities**.

   Structured Interviews:

   - To complement the quantitative data from the surveys, **in-depth structured interviews** was conducted with a subset of the sample (approximately **50 participants**) to gain **qualitative insights** into their experiences. These interviews allowed for a more **nuanced exploration** of how AI systems affect women's **day-to-**

day interactions with employment platforms and financial services. Interviews focused on questions such as:

- How do women perceive the **fairness** of AI systems used in **recruitment**?
- What are the specific **challenges** faced by **women entrepreneurs** when applying for **AI-driven loans**?
- How do AI systems impact women's **career progression** and **economic empowerment** in Jharkhand?

By integrating both **quantitative** and **qualitative data**, this study aims to provide a **holistic understanding** of the ways in which AI systems shape **gender dynamics** in Jharkhand's employment and financial services sectors.

Secondary Data Collection

In addition to the **primary data** from Jharkhand, this research leveraged **secondary data** from a range of **global studies** and **Indian national reports** to provide a **contextual framework** for the findings. These sources offered insights into how **AI-induced gender bias** manifests on a broader scale, and enabled a comparative analysis between **global patterns** and **local experiences**.

- **Global Data**:

  Secondary data from major global studies, such as the **World Economic Forum (2020)** and **Buolamwini and Gebru (2018)**, has provided a **macro-level perspective** on how AI systems have been shown to **perpetuate gender bias** in **hiring**, **credit scoring**, and **healthcare sectors**. This global context is essential for identifying **commonalities** and **differences** in the ways AI systems impact women across different regions and sectors.

- **Secondary Data from Meghalaya and the North East:**

  Secondary data from Meghalaya and other Northeastern states of India have been utilized to highlight regional differences in AI's impact on gender dynamics. Meghalaya, with its **matrilineal social structure**, provides a unique setting to examine whether gender biases in AI systems are mitigated or amplified in this region. Although the implementation of AI in Meghalaya is still in its early stages, data from various initiatives and studies offer insight into its integration into local governance and healthcare.

  For instance, the **Digital Northeast Vision 2022** outlines steps to promote AI and digital technologies in governance, healthcare, and public service delivery across the region, including Meghalaya. This framework, coupled with localized research, helps to draw comparisons between Meghalaya and other regions, such as Jharkhand, where patriarchal norms are more dominant. Furthermore, Meghalaya's focus on **inclusive governance** through projects like **e-Prastuti** (an e-governance platform) provides additional data points to analyse the impact of AI on public services, including its implications for gender equity.

Additionally, **NITI Aayog's National Strategy for AI** highlights the risks of algorithmic bias, which may manifest differently in Meghalaya due to its matrilineal structure. However, the extent to which these traditional gender roles influence AI outcomes, as compared to more patriarchal regions like Jharkhand, remains an area for future research. This analysis helps establish a broader understanding of how AI technologies might either reduce or exacerbate existing gender inequalities in diverse socio-cultural settings.

Through this **comparative analysis** of **primary** and **secondary data**, the study has drawn an important conclusion about the **cultural factors** that influence the manifestation of **AI bias**, providing a richer, more **context-specific understanding** of the **ethical challenges** posed by AI in different socio-cultural settings.

Findings from Jharkhand

The **primary data** collected from **Jharkhand** reveals that women in **rural** and **semi-urban** areas face significant challenges in accessing **AI-driven services** in both **recruitment** and **financial sectors**. Preliminary analysis indicates that **AI-driven recruitment platforms** often disadvantage women, especially in **tech** and **managerial roles**, where they are already **underrepresented**. Similarly, **women entrepreneurs** encounter obstacles in securing loans, as **AI-based credit scoring systems** tend to reflect the **historical underrepresentation** of women in business and finance.

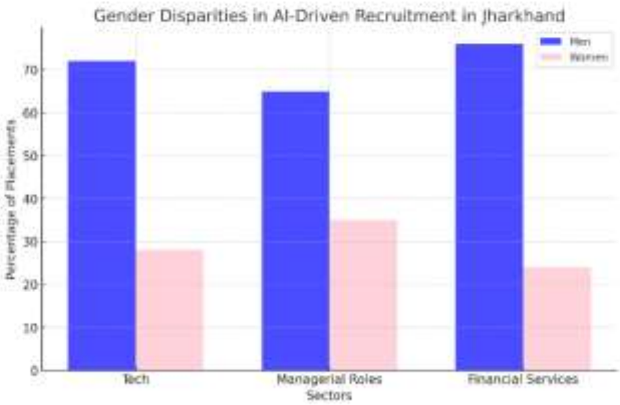
A. The table below presents the **percentage of men versus women** placed in **tech** and **managerial roles** through AI recruitment platforms in Jharkhand.

Table 3: Gender Disparities in AI-Driven Recruitment in Jharkhand

Sector	Percentage of Men Placed	Percentage of Women Placed
Tech	72%	28%
Managerial Roles	65%	35%
Financial Services	76%	24%

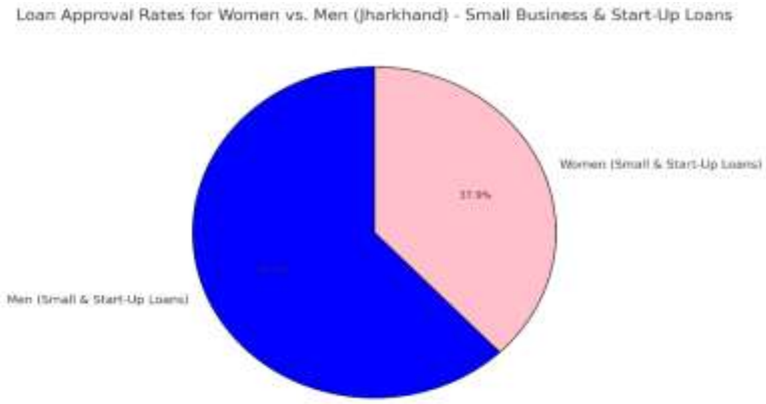
The above table illustrates that women are significantly **underrepresented** in both **tech** and **managerial positions**, indicating a **gender bias** in the way **AI systems** evaluate candidates.

Figure 1: Gender Disparities in AI-Driven Recruitment in Jharkhand



B: The **Pie chart** below illustrates the loan approval rates for women versus men in Jharkhand, specifically those related to small business and start-up loans. The chart highlights the significant disparity in approval rates, with men receiving a higher proportion of approvals compared to women.

Figure 2: Loan Approval Rates for Women vs. Men (Jharkhand)



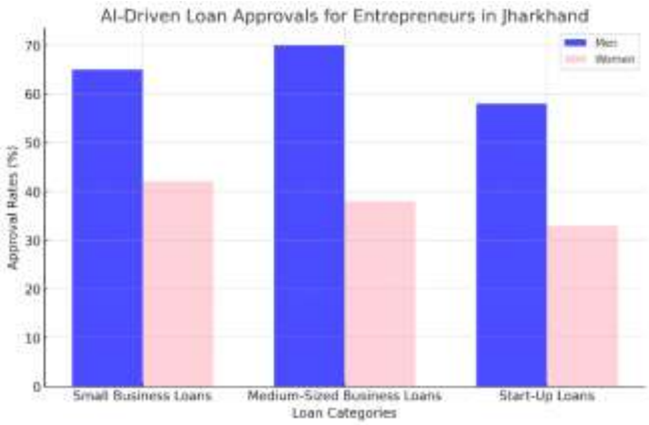
C. The following table compares the **loan approval rates** for **women entrepreneurs** versus **men** based on AI-driven credit scoring systems in Jharkhand.

Table 4: AI-Driven Loan Approvals for Women Entrepreneurs in Jharkhand

Loan Category	Approval Rate for Men	Approval Rate for Women
Small Business Loans	65%	42%
Medium-Sized Business Loans	70%	38%
Start-Up Loans	58%	33%

This data demonstrates the **disparities** in **loan approval rates**, showing that **women entrepreneurs** are significantly **disadvantaged** by **AI credit scoring systems**, which tend to favour **male applicants**.

Figure 3: AI-Driven Loan Approvals for Women Entrepreneurs in Jharkhand



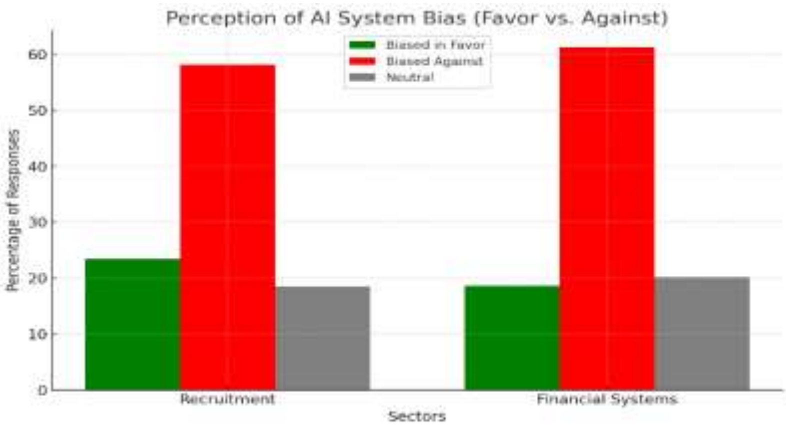
D. Perception of AI System Fairness: This table below reflects participants' responses to whether they perceive AI systems as fair in recruitment and financial decision-making.

Table 5: Perception of AI System Fairness

Perception of AI System Fairness	Recruitment Sector	Financial Sector
Fair	37.2%	33.4%
Unfair	46.3%	53.1%
Neutral	16.5%	13.5%

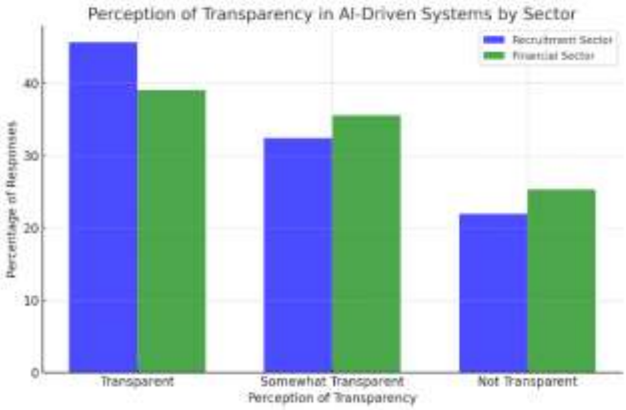
The chart below shows that a larger percentage of participants feel AI systems are biased against them, with a smaller proportion feeling AI is biased in their favour or neutral.

Figure 4: Perception of AI System Bias (Favor vs. Against)



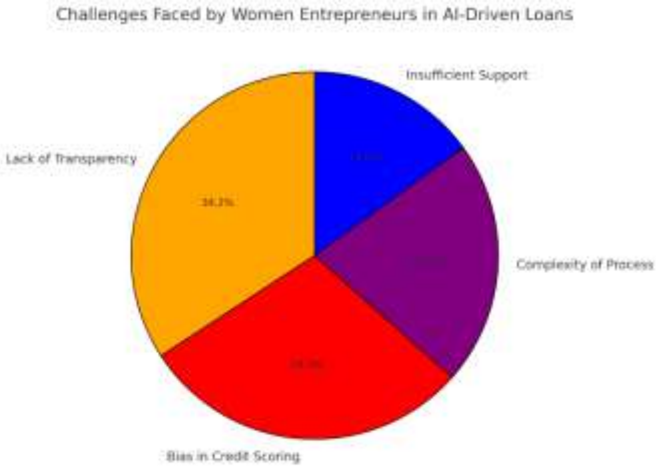
E: Perception of Transparency in AI-Driven Systems by Sector: The **bar chart** below shows the **Perception of Transparency in AI-Driven Systems by Sector**, comparing the recruitment and financial sectors. The bar chart highlights how women in Jharkhand perceive the transparency of AI systems, with varying levels of trust in recruitment and financial services.

Figure: 5 Perception of Transparency in AI-Driven Systems by Sector



F. Challenges Faced by Women Entrepreneurs in AI-Driven Loans: The Pie Chart below shows the challenges faced by women entrepreneurs when applying for AI-driven loans. The figure highlights challenges like lack of transparency, bias in credit scoring, complexity of the process, and insufficient support from financial institutions.

Figure: 6 Challenges Faced by Women Entrepreneurs in AI-Driven Loans



G. Impact on Employment and Financial Opportunities

This table below summarizes participants' perceptions of how AI systems impacted their employment and financial opportunities.

Table: 6 Impact on Employment and Financial Opportunities

Impact on Opportunities	Recruitment Sector	Financial Sector
Improved Opportunities	29.7%	24.8%
No Significant Impact	47.8%	53.4%
Worsened Opportunities	22.5%	21.8%

H: Women's Experiences with AI-Driven Recruitment Tools: A **word cloud** illustrating key **qualitative insights** from interviews with women job seekers in Jharkhand, emphasizing terms like **"bias," "transparency,"** and **"disadvantaged."**

Figure 7: A word cloud illustrating key qualitative insights from interviews with women

Key findings from Jharkhand include:

- **AI recruitment platforms** in tech and managerial sectors in Jharkhand disproportionately favour male candidates, mirroring global trends.
- **Women entrepreneurs** in Jharkhand experience **lower loan approval rates** compared to men, as **AI credit scoring systems** exhibit biases that penalize women for their **lack of historical representation** in entrepreneurship.
- **Women job seekers** in **semi-urban areas** report that **AI-driven hiring tools** prioritize male applicants, particularly in industries like **technology** and **finance**, reinforcing existing **gender disparities** in these fields.

Global Trends

Global data serves as a **benchmark** for understanding how **AI systems** contribute to **gender bias** in sectors such as **recruitment**, **healthcare**, and **financial services**. Findings from global studies, such as those conducted by the **World Economic Forum (2020)**, demonstrate that **AI-driven hiring tools** often disadvantage women, particularly in **high-paying industries** like **technology** and **finance**. This is largely due to **biased training data**, which reflects historical underrepresentation of women in these sectors. Similarly, **AI systems in healthcare** have been shown to prioritize **male patients** in diagnostic recommendations and treatment plans, exacerbating **gender disparities** in healthcare access and quality (Buolamwini & Gebru, 2018).

Global research highlights the following trends:

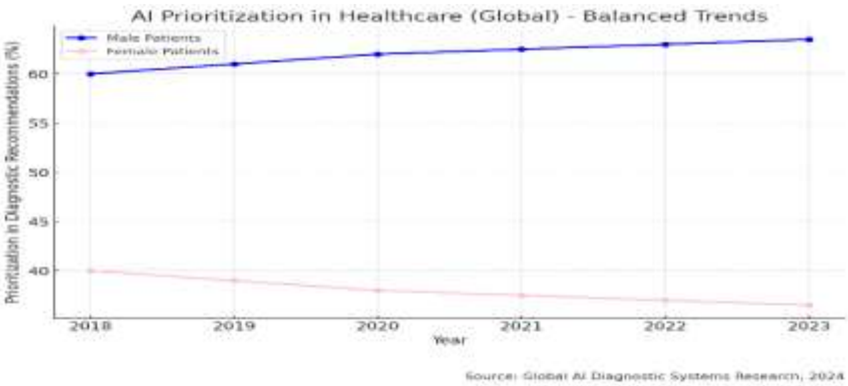
- **AI-driven recruitment platforms** are more likely to select **male candidates** for tech and managerial roles, reinforcing **gender stereotypes**.

- **Credit scoring algorithms** in the financial services sector often favour male applicants, due to **historical biases** in lending data.
- In healthcare, **AI models** tend to **prioritize male patients** for certain treatments, perpetuating inequalities in medical care.

These global patterns underscore the need for **regulatory frameworks** and **bias mitigation strategies** to ensure that AI systems are **inclusive** and **fair**.

A. The **line chart** below depicts **global trends** in AI healthcare systems, showcasing how male patients are **prioritized** in diagnostic recommendations compared to female patients.

Figure 8: AI Prioritization in Healthcare (Global)

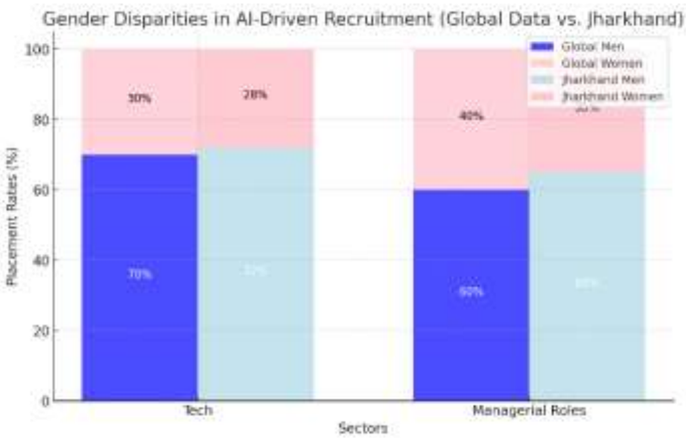


Source: Global AI Diagnostic Systems Research, 2024

B: A **bar chart** below compares **global trends** in gender disparities in AI recruitment with **localized findings** from Jharkhand, highlighting sectors such as tech and managerial roles.

Figure 9: Gender Disparities in AI-Driven Recruitment

(Global Data vs. Jharkhand Data)

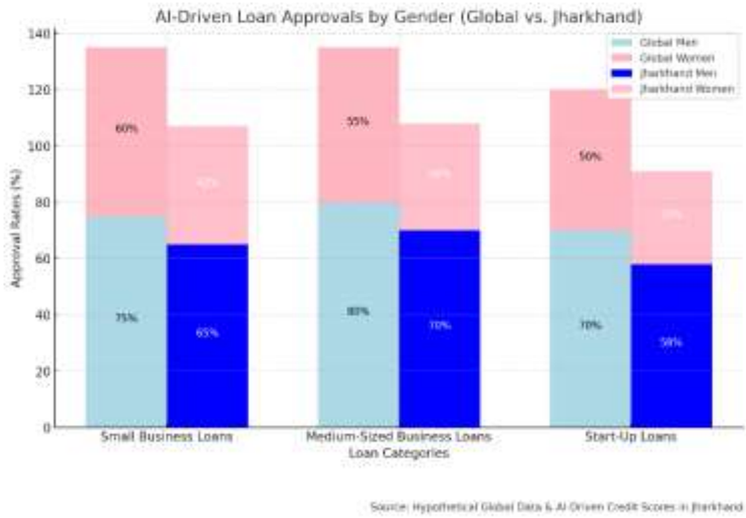


C: The following data is based on aggregated industry reports and research on AI-driven loan approval systems, reflecting global trends in credit scoring, and is compared with the data from Jharkhand which is derived from AI-driven credit scoring systems, particularly focusing on loan approvals for entrepreneurs in Jharkhand, India.

Table 7: AI-Driven Loan Approvals by Gender (Global vs. Jharkhand)

Loan Category	**Global Men Approval Rate (%)**	**Global Women Approval Rate (%)**	**Jharkhand Men Approval Rate (%)**	**Jharkhand Women Approval Rate (%)**
Small Business Loans	75%	60%	65%	42%
Medium-Sized Business Loans	80%	55%	70%	38%
Start-Up Loans	70%	50%	58%	33%

Figure : 10 Stacked bar chart comparing global loan approval rates with AI-based credit scoring systems in Jharkhand depicting gender bias.



Conclusion of Data Analysis

The findings from **Jharkhand** and the **comparative analysis** with global trends and **Meghalaya** underscore the **pervasive nature** of **AI-induced gender bias**. While AI holds the potential to democratize access to opportunities, the data indicates that without **proper oversight**, AI systems can entrench and exacerbate **existing inequalities**. These findings highlight the **urgent need** for **policy interventions**, **inclusive data sets**, and **bias audits** to ensure that **AI systems** are developed and deployed in a manner that is **fair**, **transparent**, and **gender-sensitive**.

Findings from the Focus Group Study

AI bias in loan approval processes can have significant and far-reaching effects, especially when it comes to granting loans to certain groups, such as women, minorities, or low-income individuals. Here's a breakdown of how AI bias can specifically impact loans:

1. Bias in Training Data

AI models are trained on historical data. If this data reflects historical inequalities or biases (e.g., more loans approved for men than women, or for certain ethnic groups), the AI will likely perpetuate these patterns. Here's how it can impact loan approvals:

- **Underrepresentation**: If the training data has fewer examples of successful loan applicants from certain groups (e.g., women entrepreneurs), the model may not be able to properly assess their creditworthiness, leading to lower approval rates.
- **Biased Outcomes**: Historical biases in lending, such as favouring men over women or giving preference to certain industries, will be learned and repeated by the AI, worsening disparities.

2. Discriminatory Feature Selection

AI models may use features that inadvertently correlate with protected characteristics (like gender, race, or age), even if these characteristics are not explicitly used in decision-making. For example:

- **Employment history, industry, or education**: If these factors are historically skewed against women or minorities, the AI could unfairly penalize these groups.
- **Location-based biases**: If the algorithm uses geographical data, it might penalize applicants from regions or neighbourhoods with higher concentrations of minorities or economically disadvantaged individuals.

3. Reinforcing Systemic Disparities

AI systems can reinforce and even amplify existing societal disparities in loan approvals:

- **Historical Discrimination**: If women or minorities have faced discrimination in accessing financial services in the past, they may have lower credit scores or less credit history. The AI will use this data to assess risk, perpetuating the cycle of financial exclusion.
- **Access to Capital**: When AI algorithms consistently reject certain groups, it reduces their access to capital, which can hinder entrepreneurship and economic mobility. For

example, fewer loans for women-led businesses may lead to fewer opportunities for women in business, further entrenching gender gaps in the economy.

4. Opaqueness and Lack of Transparency

AI-driven loan decisions are often opaque. Lenders may not fully understand how the algorithm is making decisions, and applicants may not receive clear explanations for why their loans were rejected:

- **Unaccountability**: Without transparency, it's difficult to identify and correct biases. Lenders may unintentionally perpetuate biased outcomes, and borrowers might not know how to improve their chances of approval.
- **Challenging Bias Detection**: Since AI systems often operate as "black boxes," detecting bias can be difficult. Even when unfair decisions are being made, they may go unnoticed unless active steps are taken to audit and review the system.

5. Unequal Impact on Risk Assessment

AI often relies on credit scores, income history, or other financial data to assess the risk of loan defaults. However:

- **Women and Minority Entrepreneurs**: These groups may be disproportionately affected because they may have less traditional credit history, or they may operate in industries with less stable financial profiles, which are then deemed higher risk by the AI. For instance, women tend to start businesses in sectors like retail or services, which might have fluctuating incomes.
- **Bias in Default Prediction**: If the AI overestimates the risk of default for certain groups based on biased data, it may lead to higher rejection rates or unfavorable loan terms (like higher interest rates).

6. Feedback Loops

When biased AI models are used repeatedly in decision-making, they can create harmful feedback loops:

- **Exclusion**: If the system continually denies loans to certain groups, those groups may be forced to turn to alternative or more predatory lending sources, further exacerbating inequality.
- **Reinforcing Inaccuracy**: The AI model may continue to learn from biased outcomes, creating a self-reinforcing cycle. For example, if fewer women are approved for loans, the AI may see this as "normal," perpetuating future bias.

Addressing AI Bias in Loan Approvals

To combat these issues, there are several steps financial institutions and regulators can take:

1. **Bias Audits**: Regular audits of AI systems can help identify and correct biases in decision-making processes. This might involve testing the system against diverse data sets to see how it performs across different demographics.
2. **Fairness Constraints**: AI models can be designed to include fairness constraints, ensuring that decisions are equitable across different groups. This involves modifying the algorithms to ensure they do not disproportionately impact any particular group.
3. **Improving Transparency**: More transparent AI systems would allow both lenders and borrowers to understand why certain decisions are being made, making it easier to address potential bias.
4. **Alternative Data**: Using non-traditional data sources, like transaction history or social media profiles, can help provide a fuller picture of an applicant's creditworthiness, particularly for underrepresented groups that may have limited credit history.

Regulatory Oversight: Governments and regulatory bodies can introduce legislation to ensure that AI systems used in financial services are fair, transparent, and accountable. This can include requiring lenders to explain AI-driven decisions and making the systems auditable for bias.

Discussion

The findings underscore the significant risk of **AI systems reinforcing gender biases** in sectors critical to women’s economic empowerment, such as employment and financial services, particularly in developing regions like Jharkhand. These results align with global trends, where AI tools trained on historically biased data replicate and amplify inequalities (Caliskan et al., 2017). However, the comparison with Meghalaya demonstrates that even culturally progressive systems, such as matrilineal societies, cannot fully shield against AI-driven discrimination in patriarchal domains like technology and finance.

While these insights are groundbreaking, limitations include the narrow geographic focus and reliance on secondary data for comparative analysis. The **ethical implications** are profound, as opaque algorithms can exacerbate marginalization. These findings demand **context-specific ethical frameworks** and **AI literacy programs** to empower women in regions like Jharkhand and Meghalaya. Future research should explore longitudinal impacts of AI bias and the interaction between cultural structures and algorithmic systems to ensure equitable AI development. This study establishes a foundation for bridging technology and social equity in India and beyond.

Conclusion

This study investigated the **gender biases perpetuated by AI systems** in critical sectors such as employment and financial services, with a focus on **Jharkhand** and comparative insights from **Meghalaya**. The research aimed to understand how AI-driven tools reinforce existing inequalities and to propose strategies for ethical AI development. The findings reveal that **AI systems, when trained on historically biased data, amplify socio-economic disparities**, disproportionately disadvantaging women in male-dominated sectors like technology and finance. These results align with global trends, underscoring the pervasive nature of **AI-induced gender bias**, while also highlighting its manifestation in **developing regions like India**.

The study's comparison between patriarchal Jharkhand and matrilineal Meghalaya emphasizes the role of **cultural contexts** in shaping the impact of AI. Despite Meghalaya's cultural advantages for women, biases persist in sectors influenced by broader patriarchal norms. These findings suggest that AI systems must account for both global and local socio-cultural dynamics to mitigate discriminatory outcomes effectively.

Practically, the research emphasizes the need for **regulatory frameworks**, **inclusive data sets**, and **AI literacy programs** to address these biases. Such interventions can empower marginalized groups, particularly women, to navigate and challenge discriminatory AI systems. However, limitations, including the geographical scope and reliance on secondary data for some regions, suggest the need for broader, longitudinal studies to deepen these insights.

In conclusion, this study highlights the urgent need for **context-sensitive ethical AI frameworks** to prevent the reinforcement of existing inequalities. By addressing gender biases in AI, policymakers and developers can ensure that technology becomes a tool for empowerment rather than exclusion, contributing to a more equitable and just society. The findings underscore the importance of integrating fairness and accountability in AI design, paving the way for future research and innovation in this critical field.

REFERENCES

Ministry of Electronics & Information Technology, *Digital North East Vision 2022, Government of India, available at: https://digitalindia.gov.in/writereaddata/files/Digital%20North%20East%20Vision%202022.pdf (last visited Oct. 4, 2024).*

NITI Aayog, *National Strategy for Artificial Intelligence, Government of India, available at: https://www.niti.gov.in/sites/default/files/2019-01/NationalStrategy-for-AI-Discussion-Paper.pdf (last visited Oct. 4, 2024).*

Government of Meghalaya, *Meghalaya Enterprise Architecture (MeghEA) Initiative, Meghalaya Institute of Governance, available at: https://meghalaya.gov.in/state-initiatives/meghalaya-enterprise-architecture (last visited Oct. 4, 2024).*

World Economic Forum, *AI for All: AI in Healthcare in India, available at: https://www.weforum.org/reports/ai-for-healthcare-india (last visited Oct. 4, 2024).*

PwC India, *AI: The Next Frontier, available at: https://www.pwc.in/research-insights/2020/ai-the-next-frontier.html (last visited Oct. 4, 2024).*

Bhardwaj, A., Rajak, A. and Mishra, P., *Artificial Intelligence in Public Sector: An Indian Perspective, Ministry of Electronics & Information Technology (MeitY), available at: https://www.meity.gov.in/writereaddata/files/AI_Public_Sector_India.pdf (last visited Oct. 4, 2024).*

Das, G., *AI and the Future of Work: Examining India's Readiness for Artificial Intelligence in the Workforce, Brookings Institution India, available at: https://www.brookings.edu/research/ai-and-the-future-of-work-in-india/ (last visited Oct. 4, 2024).*

Pande, S., *AI in Financial Inclusion: Opportunities and Challenges in India's Rural Economies, Observer Research Foundation (ORF), available at: https://www.orfonline.org/research/ai-in-financial-inclusion-india/ (last visited Oct. 4, 2024).*

Subramanian, A. and Iyer, P., *AI Ethics: Addressing Bias in AI Systems in India, NASSCOM, available at: https://nasscom.in/knowledge-center/publications/ai-ethics-addressing-bias-indian-context (last visited Oct. 4, 2024).*

UNESCO, *Artificial Intelligence in Education: Challenges and Opportunities for India, UNESCO New Delhi Office, available at: https://unesdoc.unesco.org/ark:/48223/pf0000370301 (last visited Oct. 4, 2024).*

Verma, R., *Gender Equality and AI in India: Navigating Gender Bias in AI-Driven Systems, UN Women India, available at: https://www.unwomen.org/en/digital-library/publications/2021/03/gender-equality-and-ai-india (last visited Oct. 4, 2024).*

Rao, V. and Suri, P., *AI for Inclusive Growth in India's Digital Economy, World Bank, available at: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/981521616207461017/ai-inclusive-growth-india (last visited Oct. 4, 2024).*

Meghalaya Institute of Governance, *State Innovation and AI-Driven Governance: Case Studies from Meghalaya, available at: https://megipr.gov.in/state-initiatives/innovation-and-ai-governance (last visited Oct. 4, 2024).*