ISSN: 2277-8985

VOLUME 15 ISSUE 1 MARCH 2026

AWADH INTERNATIONAL JOURNAL OF INFORMATION TECHNOLOGY AND EDUCATION (AIJITE)

(Peer Reviewed, Refereed Journal)

alfa Publications

New Delhi (India)

Awadh International Journal of Information Technology and Education (AIJITE)

(Peer Reviewed Refereed Journal)

alfa ***Publications***

NEW DELHI (INDIA)

INSTITUTE OF VOCATIONAL STUDIES
PRINCIPAL

Awadh International Journal of Information Technology and Education

(Peer Reviewed Refereed Journal)

ISSN : 2277-8985

Published by: Shilpa Goel
for
ALFA PUBLICATIONS
4398/5, Ansari Road, Daryaganj,
New Delhi - 110 002
Phone: +91-11-23275092
e-mail: alfapublications@gmail.com

© Awadh Centre of Education
(COMM-IT Career Academy & Institute of Vocational Studies)
Awadh Bhavan,
FC-31, Sheikh Sarai, Phase - II
Institutional Area,
New Delhi - 110017, India

Vol. 15 Issue 1, March 2026
Periodicity of Publication, Biannual

SUBSCRIPTIONS

Awadh International Journal of Information Technology & Education is published twice a year. All orders accompanied with payment should be sent directly to: **Alfa Publications**, 4398/5, Ansari Road, Daryaganj, New Delhi - 110002

ANNUAL SUBSCRIPTION CHARGES

TWO ISSUES Rs. 1500.00 / $ 100.00 (Overseas)

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Awadh International Journal of Information Technology and Education

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Awadh International Journal of Information Technology and Education
ISSN : 2277-8985
Vol. 15, Issue -1 March 2026
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AI and Social Inequality: Ethical Implications for Digital Society

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ABSTRACT

The integration of AI into modern society acts as a "double-edged sword." On one side, it brings efficiency and innovation, while on other side, it deepens social inequality by automating jobs, concentrating wealth in tech-heavy regions, and embedding human biases into automated decision-making systems. The benefits of AI are currently distributed unevenly, potentially widening the gap between different socio-economic groups. This paper explores the ethical challenges posed by AI within a digital society, focusing on how algorithmic bias, the "M-shaped" economic divergence, and the deepening digital divide; reinforces existing systemic inequities. This study examines the mechanisms through which AI automates discrimination in hiring, finance, and healthcare, while simultaneously hollowing out the middle class through automation, by synthesizing recent data from 2024–2026. The paper concludes that unless we implement strong, interdisciplinary governance and ensure that AI resources are democratically shared, the technology will stop being a tool for progress. Instead, it will become a permanent structure that reinforces and hardens social class divisions (stratification).

Keywords: Digital Divide, AI Bias, Algorithmic Bias, M Shaped Economy.

INTRODUCTION

Artificial Intelligence, in today's scenario, has shifted from a niche tool to a core societal infrastructure i.e. AI is now a foundational part of the digital world and not just an opinion

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existing social biases and inequalities. AI frequently acts as a "mirror of inequality," rather being neutral. It reflects and amplifies the biases of its creators and the datasets upon which it is built (PrometAI, 2026). In other words, it is creating an inequality gap which is a "Next Great Divergence," where a significant ethical and power gap grows between those who own the algorithms and those subject to their decisions.

ALGORITHMIC BIAS: CRITICAL ETHICAL CHALLENGE IN MODERN TECHNOLOGY

The core argument is that AI systems are not inherently neutral. They are trained on historical data and act as a mirror to the past—mathematically absorbing and replicating existing human prejudices. Instead of eliminating bias, these algorithms often use their accuracy to reinforce systemic social inequalities under the pretext of objective data. These systems can unintentionally automate and scale discrimination in areas like hiring, lending, or law enforcement.

JUDICIAL AND POLICING BIAS

According to Russell & Norvig, (2021), data-driven technology can unintentionally entrench existing social inequalities within the legal system. It highlights a cycle where historical biases are "baked into" software, leading to real-world consequences for specific communities.

To understand the above bias better, lets see the black box problem. In computer science, a black box is a system where you can see the input and the output, but the internal logic (the "why") is hidden or too complex for humans to understand. If a judge uses an AI to determine if a defendant (Culprit) is a flight risk, they may not know exactly which factors the AI used to reach its conclusion. AI doesn't follow a simple "If-Then" script written by a human; instead, it identifies patterns across millions of data points that are mathematically too dense for a human judge to parse in a courtroom. Also, since the logic is opaque, the defendant cannot challenge the decision in court. There is lack of Accountability to flag them as "high risk".

Many modern algorithms are programmed to be "race-blind", to avoid bias, meaning they lack a "Race" data field. Engineers often exclude race data to *prevent* bias (the "colorblind" approach), but the algorithm "reconstructs" race through metadata like ZIP codes or education levels. AI "reconstruct" race using Proxies — i.e. data points that are statistically linked to protected demographics. Common proxies include:

- Socioeconomic Status: Unstable employment history or low income.
- ZIP Codes: Due to historical red-lining and housing patterns, certain ZIP codes correlate almost perfectly with specific racial demographics.

When an AI concludes that "People from ZIP code 10001 are likely to re-offend," it is effectively using race as a risk factor without ever "knowing" the person's race. This creates a neutrality

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fallacy: the system appears fair because it doesn't "see" color, yet its outcomes remain racially skewed.

THE RECURSIVE FEEDBACK LOOP

While proxies affect the individual's risk score, these scores aggregate to dictate police resource allocation, leading to the Recursive Loop. The individual bias scales up into a systemic, self-fulfilling prophecy known as a Recursive Loop.

For example, suppose Police have historically patrolled Neighborhood A more than Neighborhood B and Increased Arrests are made from neighborhood A because there are more police in Neighborhood A, more crimes (even minor ones like loitering or petty theft) are recorded there. Now, the AI analyses the data and sees a "high crime rate" in Neighborhood A. The AI tells the police to send *more* officers to Neighborhood A. More officers lead to more arrests, which creates more "data," confirming the AI's initial bias and starting the cycle again.

STATISTICAL EVIDENCE: THE COMPAS STUDY

The real-world consequences of these gaps were documented in a landmark 2016 ProPublica study of the COMPAS risk assessment tool. The study revealed that even when controlling for prior crimes, the algorithm was significantly biased:

Table 1 Showing AI bias in controlling crimes

Metric	Black Defendants	White Defendants
False Positives (Incorrectly labelled High Risk)	**44.9%**	23.5%
False Negatives (Incorrectly labelled Low Risk)	28.0%	**47.7%**

THE GENDER AND RACIAL GAP IN RECOGNITION

Another critical issue in modern AI development algorithmic bias is that its facial recognition technology has advanced rapidly but its accuracy is not distributed equally across different demographic groups. (PwC, 2022; UNESCO, 2026). Think of it like a camera that was only tested in bright sunlight; when you take it into the shade, it struggles to capture a clear picture. In the world of AI, this "struggle", results in algorithmic bias. Here is a simple breakdown of why this happens and what the numbers actually mean.

The primary reason is the Training Data. To teach an AI to recognize faces, developers show it millions of photos. Historically, these photo collections (datasets) have been made up mostly of white men. Because the AI "learned" what a face looks like primarily from one group, it becomes an expert at identifying those specific features. When it encounters faces with different skin tones or bone structures, it hasn't had enough "practice," leading to higher mistake rates.

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The "Error Rate" represents how often the AI fails to correctly identify or detect a person. As shown in the research from UNESCO and the *Gender Shades* project, the gap between the most-recognized and least-recognized groups is significant:

Table 2: AI shows error with Gender and Race

Demographic Group	**Error Rate (Lower is Better)**	**What this means**
Lighter-skinned Men	0.0% – 0.8%	The AI is almost perfect; it rarely makes a mistake.
Lighter-skinned Women	0.1% – 7.0%	Mostly accurate, but errors begin to appear.
Darker-skinned Men	1.0% – 12.0%	The AI is significantly more likely to misidentify these individuals.
Darker-skinned Women	20.0% – 34.0%	In the worst cases, the AI fails 1 out of every 3 times.

This isn't just a technical glitch; it has "real-world" consequences. If a phone's face-unlock feature fails, it's an annoyance. It can have dangerous consequences. In the context of self-driving cars, if the sensors are less accurate at spotting pedestrians with darker skin, the car might not brake in time. This creates a situation where a person's physical safety depends on their skin tone.

Similarly, if AI is used by law enforcement or for airport security, a high error rate for darker-skinned women can lead to wrongful accusations or invasive questioning simply because the software couldn't "read" their face correctly.

Similarly, if a bank uses Face ID to let you into your account, but the software has a high error rate for your demographic, you are effectively locked out of your own money and digital services.

THE ECONOMIC M-CURVE: JOB DISPLACEMENT AND WEALTH CONCENTRATION

The AI revolution is fundamentally altering the labour market. Economists observe an "M-shaped" economy where wealth clusters at the extremes—high-tech creators and low-wage service workers—while the middle class is hollowed out (PrometAI, 2026).

Job Displacement: The Economic M-Curve is a way of describing how Artificial Intelligence is changing the job market and who gets the most money. In a healthy economy, most people sit in the middle (the "Bell Curve"). But with AI, that middle is disappearing, leaving two groups at the opposite ends of the spectrum—looking like the letter M.

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The Hollowing of the Middle (The Valley): The "dip" in the middle of the M represents middle-class jobs that are being lost. These are usually "routine" jobs—tasks that follow a predictable pattern. Because AI is great at patterns, it can do these jobs faster and cheaper than humans.

Examples: Data entry, basic accounting, paralegal work, and factory assembly.

The Result: These workers are forced to move toward one of the two "peaks" of the M.

The High-Tech "Alpha" Peak (The Left Side): On one side of the M, wealth is piling up for the people who create or own the technology.

Who is here? AI developers, data scientists, and business owners who use AI to make huge profits with very few employees.

The Result: This group sees their wealth grow rapidly because their skills are rare and highly valuable in an AI-driven world.

The Low-Wage Service Peak (The Right Side): On the other side of the M, there are many jobs that AI *cannot* do yet. These usually require physical movement in messy environments or deep human emotion.

Who is here? Home healthcare workers, janitors, and childcare providers.

The Result: While these jobs are "safe" from being replaced by robots, they often pay much less than the old middle-class jobs did.

Wealth Concentration - The M-Curve shows a serious problem: as AI makes the world more productive, the money doesn't spread out to everyone. Instead:

- The money flows to the top (the creators and owners).
- The middle class is pushed down into lower-paying service jobs.

This creates a "bipolar economy" where the gap between the rich and everyone else gets wider, making it much harder for people to improve their lives and move up the social ladder.

GEOGRAPHIC AND GENDER DISPARITIES

This section highlights how the benefits and risks of AI are not distributed equally, creating two distinct types of "divides": Geographic and Gender-based. (UNDP, 2025). AI isn't affecting everyone the same way. While it brings a lot of progress, it is also creating new "divides" or gaps between different groups of people based on where they live, their gender, and their access to technology. AI is creating a "winner-take-all" situation where some people get ahead while others struggle to keep up.

- **The Geographic Divide (Place):**



Big cities with lots of tech and smart workers (like Silicon Valley) are getting richer and faster. Smaller towns or areas that rely on old-school factory work are losing jobs to automation and getting "left behind."

- **The Gender Gap (Work):**

Women are at higher risk because many hold "office" or "service" jobs (like scheduling or data entry) that AI is very good at doing. Without training for new roles, women could lose the progress they've made in the workplace over the last few decades.

AI AUTOMATES DISCRIMINATION IN FINANCE, HEALTHCARE, EDUCATION AND MANUFACTURING

The table breaks down how AI impacts specific industries, emphasizing that "Exposure" doesn't just mean job loss—it also means systemic unfairness.

Table 3: AI Exposure and Job Displacement Risk by Sector (2025-2026)

Sector	The Risk	The Unfairness Factor
Finance	AI decides who gets a loan.	If the AI is biased, poor people might be blocked from borrowing money, keeping them in poverty.
Healthcare	AI helps doctors diagnose diseases.	Rich hospitals get "Super AI," while country clinics don't. This creates two levels of health quality.
Education	AI tutors help students learn.	Rich kids get "Premium AI" tutors and get smarter faster; kids who can't afford it fall behind.
Manufacturing	Robots do physical work.	Factory workers lose their jobs directly as robots take over manual labor.

DIGITAL DIVIDE 2.0: THE NEW RULES

The "Digital Divide" is no longer just about who has an internet connection; it has evolved into a deeper gap - involving power, language, and data. The Digital Divide 2.0 is the gap between those who build and understand AI and those who merely provide the data for it.

Beyond the Connection: AI & Compute Sovereignty

In the past, the "divide" was about having a laptop or Wi-Fi. Today, the gap is defined by AI Literacy (knowing how to use AI) and Compute Sovereignty (having the actual supercomputers and data to build your own AI).

- The Passive Consumer: Many countries only use AI built by others. This means they rely on foreign rules, foreign values, and foreign tech support.
- The Sovereign Builder: Nations that train their own models can ensure the AI understands their specific laws, culture, and economy.

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The Global South vs. The Global North

There is a growing productivity gap between wealthy tech hubs and developing nations.

- Data Exclusion: If an AI is trained mostly on data from wealthy cities in the North, it won't know how to help a farmer in a rural village in the South.
- The Risk: When indigenous or rural communities are left out of the "training data," the AI might give them advice that is useless or even culturally insensitive (United Nations, 2025).

The Linguistic Barrier

Language is the primary way we interact with AI, but most Large Language Models (LLMs) are "English-first."

- The Problem: If you speak a regional dialect or a non-Western language, the AI is often less accurate, slower, or completely unavailable. This creates a world where English speakers get "premium" intelligence while others get "inferior" service.
- The Solution: Localized projects are fighting back. For example, India's Bharat-VISTAAR (2026) is specifically designed to give rural farmers AI tools in their own native languages, ensuring they aren't left behind by the English-centric tech boom (Drishti IAS, 2026).

Table 4: Comparison between Old Digital Divide and New Digital Divide

Feature	Old Digital Divide (1.0)	New Digital Divide (2.0)
Primary Need	Physical hardware & Cables	Training data & Processing power
Main Barrier	Cost of devices	Language & AI education
Outcome	Can you get online?	Can you control your own AI?

ETHICAL FRAMEWORKS AND MITIGATION STRATEGIES

To stop AI from increasing inequality, we must move from "suggested guidelines" to "enforceable laws." Without intervention, AI will naturally consolidate power and wealth among a few elite entities, deepening societal inequality. We need legally binding rules to stop AI from making the rich richer and the powerful even more dominant. Following are the three main strategies:

Democratic Diffusion (Sharing the Power)

Right now, only massive "Big Tech" companies have the billions of dollars needed for the supercomputers (GPUs) and data centers required to build advanced AI. This creates a monopoly.

- The Simple Idea: Treat AI like water or electricity—something everyone needs access to.

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- The Action: Governments should provide "public" data and computing power to small businesses, students, and researchers.
- The Result: A local startup can compete with a global giant because the basic "ingredients" for AI are available to everyone.

Algorithmic Auditing (The Health Check)

When a company handles money, an outside accountant checks their books to make sure they aren't cheating. This strategy says we should do the same for AI code, especially in "high-risk" areas.

- The Focus: AI used for big life decisions, like who gets a job, who gets a loan, or police flagging suspects.
- The Action: Independent experts (not the company that made the AI) look under the hood. They check if the AI is being unfair to people based on their race, gender, or where they live. (Laux et al., 2024).
- Concrete Impact: For example, studies have shown that some facial recognition AI can have error rates up to 34% higher for women with darker skin compared to lighter-skinned men. Audits force companies to fix these gaps.

Human-in-the-Loop (The Human Safety Switch)

This addresses "metacognitive laziness"—the habit of humans blindly trusting a computer's answer because it seems "smarter" than us. (OECD,2026)

- The Simple Idea: Don't let the machine fly the plane alone.
- The Action: For any major decision (like a medical diagnosis or a legal ruling), a human must review the AI's work and "sign off" on it.
- The Result: It ensures that empathy, common sense, and human values are part of the final choice, which is something code cannot feel or understand.

CONCLUSION

For years, the conversation around AI has been dominated by Technological Determinism—the idea that technology is an unstoppable force that happens *to* us. This conclusion argues the opposite: technology is a choice, and its impact is a reflection of our own social values.

Technology is a Mirror, Not a Master

The argument here is that AI doesn't "invent" racism, sexism, or poverty; it simply inherits them from the data we give it. If a company uses an AI to screen resumes based on 20 years of biased hiring data, the AI will naturally learn to be biased.

- The Shift: We often blame the "algorithm" when things go wrong. This text argues we should instead look at the Social & Economic Structures that built the algorithm.

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- Agency: Because humans build these frameworks, we have the "agency" (the power) to redesign them. We can mandate transparency, diversify data, and pass laws that hold developers accountable.

Moving from "Speed" to "Intent"

In the early days of Silicon Valley, the mantra was "Move Fast and Break Things." The goal was to dominate the market first and worry about the consequences later. We are now seeing the "broken things"- ranging from the spread of misinformation to the deepening of the digital divide.

- Innovation with Purpose: This requires asking "Who is left out?" *before* the code is written.
- Example: Instead of building a generic medical AI that only works for people with high-speed internet and expensive smartphones, "Purposeful Innovation" would prioritize a tool that functions on low-bandwidth networks to help rural or underserved communties.

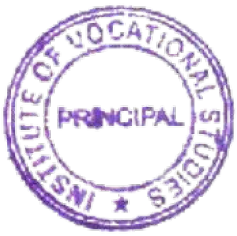
The Choice: Automate vs. Dismantle

This is the most "active" part of the text. It describes two paths for the future:

- Automating Barriers: This is "Status Quo 2.0." It's what happens when we use AI to make existing unfair systems more efficient. For instance, using AI to predict "risk" in banking based on neighborhood zip codes (which often correlate with race) effectively automates old forms of segregation.
- Dismantling Barriers: This is using AI as a "detective" or a "bridge."
    - *AI as a Detective:* Using algorithms to find hidden patterns of pay gaps in a massive corporation that humans might miss.
    - *AI as a Bridge:* Creating real-time translation tools that allow a student in a remote village to access the world's best scientific journals in their native tongue.

Table 5: Summary of the "2030s Goal"

Concept	The Old Way (Pre-2020s)	The New Goal (The 2030s)
Control	Determinism: We are passengers on the tech train.	Agency: We are the architects of the system.
Focus	Optimization: Making things faster and cheaper.	Equity: Making things fairer and more inclusive.
Outcome	Scaling Bias: Making inequality happen at "light speed."	Social Justice: Using tech to break down old walls.



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