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ARTIFICIAL INTELLIGENCE, INEQUALITIES OF KNOWLEDGE AND RESOURCES, AND SOCIO-ECONOMIC SECURITY: GLOBAL EVIDENCE WITH IMPLICATIONS FOR INDIA'S LABOR AND IT WORKFORCE

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Abstract

Artificial intelligence (AI) is increasingly embedded in production, services, and workforce management. Although AI can raise productivity and output, its distributional effects are uncertain and mediated by institutions and access to complementary resources. This paper investigates how AI may widen capability inequality—inequalities in access to knowledge, digital infrastructure, computational resources, and organizational adoption—thereby shaping income opportunities and socio-economic security for low-income groups. Using an integrative socio-technical political economy framework and validated secondary sources (OECD, ILO, UNDP, WTO, WEF) alongside official Indian statistics (NSO/MoSPI GDP estimates, PLFS, HCES) and high-reliability sector evidence (Reuters; Nasscom), the analysis is structured across past, present, and future phases. Evidence indicates accelerating AI adoption among firms in advanced economies and persistent adoption gaps among groups, suggesting unequal access to AI-enabled productivity. OECD (2026) reported, Global frameworks warn that uneven readiness may produce a "Next Great Divergence" between countries. (UNDP, 2025), (WTO, 2025), For labor markets, refined exposure measures imply widespread task transformation rather than uniform job destruction, with accelerated skill change as a central risk for vulnerable workers. (ILO, 2025) India's macro growth remains robust, yet labor-market segmentation and digital capability gaps create distributional vulnerabilities. (MoSPI–NSO, 2025) In addition, AI-driven efficiency pressures in IT services—an important mobility channel for Indian households—may compress billable work and alter hiring and wage structures, raising transition risks even for technical workers. (Reuters, 2026a) The paper proposes a policy architecture for "shared gains" centered on learning equity, transition protections, accountable algorithmic management, and distribution-sensitive metrics beyond GDP.

Keywords: Artificial Intelligence, Inequality, Digital Divide, Socio-Economic Security, Skills, Layoffs, IT Services, India.

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1. Introduction

AI adoption is accelerating across the global economy, shaping how value is created and distributed. OECD indicators show continued expansion of firm-level AI use, with reported AI adoption among firms more than doubling between 2023 and 2025 in OECD countries with available data. (OECD,2026) Such diffusion is frequently framed as productivity-enhancing and growth-promoting, yet growth does not automatically translate into equitable participation. The distributional question is therefore central: who can access AI capability and who captures its returns?

This paper argues that AI's inequality effects are best understood through capability inequality—unequal access to knowledge (education, skills), resources (digital infrastructure, compute, devices), and institutional support (workplace integration, labor protections, governance capacity). Where these complements are uneven, AI can magnify disparities in earnings, job quality, and economic security.

Global evidence warns of divergence risks. UNDP's "Next Great Divergence" analysis highlights that countries lacking infrastructure, skills, and governance readiness may experience slower AI adoption while still facing disruption, potentially widening gaps between countries. (UNDP, 2025) WTO's World Trade Report 2025 similarly frames AI as a potential engine of growth but emphasizes that inclusive outcomes depend on whether people and regions can share in AI-driven benefits. (WTO, 2025)

India is a strategically important case because it combines: (a) large low-income populations and a highly segmented labor market, and (b) a globally significant IT and technology services sector that may be exposed to AI-driven efficiency pressures. Reuters reports investor and industry concerns that AI-led automation could compress delivery timelines and reduce billable hours in traditional IT services models. (Reuters 2026a) This paper therefore integrates global evidence with India's official indicators and sector signals to examine distributional implications and policy priorities.

2. Research Objectives

To synthesize global evidence on AI adoption and its distributional channels through capability inequality.

To assess labor-market transition risks, including task automation, skill re-bundling, and restructuring in technical occupations.

To contextualize global mechanisms using India's official socio-economic indicators and India-specific IT sector evidence.

To propose policy recommendations that strengthen socio-economic security and broaden participation in AI-driven growth.

3. Hypotheses

H1 (Capability channel): Where access to education, digital infrastructure, and AI tools is unequal, AI adoption is associated with widening dispersion in earnings opportunities and job quality.

H2 (Transition channel): AI-driven task restructuring increases skill volatility and transition risks in exposed occupations, including technical and IT roles, potentially affecting wage structures and entry-level opportunities.

H3 (India channel): In India, labor-market segmentation and uneven capability access, combined with AI-driven restructuring pressures in IT services, elevate socio-economic security risks for vulnerable groups unless mitigated by targeted policy and institutional responses.

4. Literature Review

4.1 AI and wage inequality: conditional and institution-dependent

OECD's cross-country work emphasizes that AI's impact on wages and wage inequality is theoretically ambiguous: AI can automate some tasks while complementing others, and distribution outcomes depend on labor-market institutions and adoption patterns. (OECD,2024) Evidence for 2014–2018 across 19 OECD countries shows no indication that AI affected wage inequality between occupations during that period, underscoring the need to avoid deterministic claims and to focus on mechanisms and policy conditions. (OECD,2024)

4.2 Generative AI exposure and job transformation

ILO's refined global index provides task-based estimates of occupational exposure to generative AI and communicates that a substantial share of jobs is at risk of transformation. (ILO, 2025) "Transformation" can still generate inequality when skill thresholds rise faster than access to reskilling, when bargaining power weakens, or when pay compresses for tasks that become easier to automate.

WEF's Future of Jobs 2025 provides additional labor-market foresight: employers expect around 39% of key skills required in the job market to change by 2030, implying a large reskilling challenge with distributional consequences for workers with limited learning access. (WEF, 2025)

4.3 Divergence risk: AI readiness and unequal development pathways

UNDP argues that unequal readiness and uneven adoption can set in motion a "Next Great Divergence," reversing decades of convergence in development outcomes if AI benefits concentrate in high-capability economies. (UNDP, 2025) WTO similarly frames AI's relationship with trade and inclusive growth as uncertain and highlights the risk of widening divides if exclusion from benefits repeats patterns observed in earlier globalization waves. (WTO, 2025)

4.4 India's labor market and the AI transition

India's official statistics indicate improving labor force participation and employment ratios, yet the labor market remains segmented and informal for a large share of workers. PLFS 2023–24 reports LFPR 60.1%, WPR 58.2%, and UR 3.2% (usual status, 15+), which provides a baseline for assessing the security implications of future transitions. (MoSPI–NSO, 2024), (DGE Report 23-24)

Consumption inequality indicators from HCES show a decline in consumption Gini in 2023–24 compared to 2022–23 (rural and urban), suggesting recent distribution improvements in consumption terms; however, consumption inequality and future income-generation pathways may diverge under rapid technological change. (PIB, 2025), (MoSPI report 23-24).

4.5 IT and technical jobs: disruption signals and employment context

India's IT and technology services model faces potential AI-driven pressure. Reuters reports that AI-led automation threatens to compress project timelines and reduce billable hours, challenging labor-intensive delivery models. (Reuters 2026a) Reuters also reports TCS encouraging employees to use AI tools to deliver faster and cheaper services even if it reduces revenue, implying business-model adjustment that can affect hiring, wages, and role composition. (Reuters, 2026b) At the same time, employment data from Nasscom indicates the sector continues to expand in net terms, with Strategic Review reports documenting net hiring and total workforce levels (e.g., net additions and employment base). (Nasscom, 2025) This combination—continued employment growth with business-model pressure—supports the argument that the principal near-term risk is job and skill restructuring, not necessarily immediate aggregate job collapse.

5. Research gap

Mechanism integration: Many studies treat AI ethics/bias separately from income distribution; fewer integrate "capability inequality" (skills + infrastructure + compute + adoption) as a distribution mechanism.

Technical/IT job realism: Much discourse assumes technical jobs are protected; generative AI reshapes task architecture, affecting entry-level pathways and wage structures. A mechanism-based synthesis is needed.

India linkage with verified official indicators: There is limited synthesis that combines global institutional evidence with India's official labor, consumption, and growth indicators plus credible sector disruption signals.

6. Methodology

6.1 Design

This paper is an integrative secondary-data synthesis using a socio-technical political economy lens. It does not claim causal identification; instead, it triangulates validated institutional findings, official statistics, and sector evidence to map mechanisms and plausible distribution pathways.

6.2 Data sources

Global institutional sources: OECD (AI adoption; wage inequality), ILO (exposure index), UNDP (divergence), WTO (inclusive growth), WEF (skills transition).

India official sources: NSO/MoSPI GDP estimates, PLFS 2023–24, HCES 2022–23 and 2023–24.

India sector evidence: Reuters and Nasscom Strategic Review reports for IT disruption and employment context; NITI Aayog roadmap for job creation in AI economy.

Discussions at the India AI Impact Summit 2026 (New Delhi, 16–20 February 2026)

6.3 Analytical procedure

Baseline: Establish growth and distribution context (India: GDP, PLFS, HCES).

Mechanism mapping: Identify capability inequality channels (skills, infrastructure, compute, adoption). Labor transition mapping: Use ILO + WEF to frame exposure and skill instability.

India IT stress test: Use Reuters + Nasscom to analyze potential impacts on technical employment ladders. Synthesis: Derive results as evidence-backed propositions and policy implications.

7. Secondary Data Analysis

7.1 Global diffusion and the "AI capability gap"

OECD reports that in 2025, 20.2% of firms in countries with available data used AI, up from 14.2% in 2024 and 8.7% in 2023. (OECD,2026) Even at this early adoption stage, uneven distribution of AI capability is visible through unequal access to tools, training, and workplace integration. This implies that AI's productivity benefits are not uniformly accessible, creating the conditions for unequal returns.

7.2 Divergence dynamics: between-country inequality

UNDP's divergence framing emphasizes that countries with limited infrastructure and governance capacity may adopt AI slowly while facing disruptive spillovers, risking widening inequality between countries. (UNDP, 2025) WTO's 2025 report similarly warns that inclusive outcomes are not guaranteed and that the AI revolution could repeat exclusionary patterns observed in earlier trade-led growth waves if policy is not designed for inclusion. (WTO, 2025)

7.3 Labor-market exposure and skill volatility

ILO's refined exposure work underscores that a large share of jobs may be transformed rather than fully automated away, but transformation can still worsen inequality by increasing skill requirements and shifting bargaining power. (ILO, 2025) WEF reports that employers expect 39% of key job skills to change by 2030, implying that unequal reskilling access may become a major distribution mechanism. (WEF, 2025)

7.4 India baseline: growth, labor market, and consumption inequality

NSO/MoSPI's second advance estimates report real GDP growth at 6.5% for FY 2024–25 and first revised estimate of 9.2% for FY 2023–24. PLFS 2023–24 reports LFPR 60.1%, WPR 58.2%, and UR 3.2% (usual status, 15+).(MoSPI–NSO, 2024).

HCES indicates a decline in consumption Gini for rural and urban areas in 2023–24 compared to 2022–23. This suggests recent improvement in consumption distribution; however, the AI transition's main distributional risk may arise through income-generation pathways and job-quality changes, particularly for groups with weak capability access. (PIB, 2025), (MoSPI report 23-24)

7.5 India IT and technical employment: (disruption and employment context)

Reuters reports that AI-led automation could compress timelines and reduce billable hours in India's IT services model, with market-value losses and investor concern reflecting perceived business-model risk. (Reuters, 2026a) Reuters also reports TCS urging employees to use AI tools even if it cannibalizes revenue, implying accelerated adoption pressures.

Crucially, sector employment context is not one-directional. Nasscom's Strategic Review reporting indicates continued net job additions and projected employment expansion in India's tech sector (e.g., FY26E employment and net additions), suggesting reallocation and skill change rather than uniform net job loss.

Analytical implication: The most defensible near-term risk is polarization within technical roles: fewer routine entry-level tasks (testing, basic coding, documentation), higher skill thresholds, tighter hiring for "billable" roles, and stronger wage premiums for advanced AI, data, cloud, security, and domain skills.

7.6. India AI Impact Summit 2026: Inclusion, Skills, and Distributional Implications

The India AI Impact Summit 2026 (New Delhi, 16–20 February 2026) explicitly framed AI within an inclusion-oriented policy agenda centered on People, Planet, and Progress, with emphasis on "people-centric AI" for skills, service delivery, and equitable access (Press Information Bureau [PIB], 2026). This positioning is directly relevant to the present study's focus on income distribution and socio-economic security, as it acknowledges that AI's productivity gains are not distributionally neutral.

Summit discussions publicly recognized uneven employment effects across sectors, particularly for informal, gig, and early-career workers facing task reconfiguration and heightened skill volatility (Economic Times Brand Equity, 2026). These concerns are consistent with global evidence indicating widespread occupational transformation rather than uniform job destruction, with significant reskilling implications (International Labour Organization [ILO], 2025; World Economic Forum [WEF], 2025). In India's context—characterized by labor-market segmentation—such transformation risks can translate into unequal income trajectories unless supported by systematic capability expansion (Ministry of Statistics and Programme Implementation [MoSPI], 2025).

The summit also catalyzed AI-education partnerships aimed at scaling access to AI tools and curricula across higher-education institutions (Times of India, 2026). While these initiatives may reduce knowledge inequality, their distributive impact depends on reach beyond elite institutions and on complementary investments in digital infrastructure and lifelong learning.

At the governance level, summit engagements linked to the Global Partnership on AI (GPAI) and OECD cooperation reinforced principles of human-centric and trustworthy AI (Organisation for Economic Co-operation and Development [OECD], 2026). Institutional design—particularly around algorithmic accountability, labor standards, and transition support—will shape whether AI-enabled gains diffuse broadly or concentrate among high-skill workers and capital owners.

Overall, the summit underscores three propositions central to this study: (i) AI adoption entails heterogeneous income effects; (ii) capability inequality mediates distributional outcomes; and (iii) inclusive policy architecture is essential to translate AI-driven growth into durable socio-economic security.

8. Findings / Results

R1 (Capability inequality is the primary distribution channel): Evidence of uneven AI adoption and unequal readiness supports the proposition that AI tends to concentrate gains where complementary capabilities are already strong.

R2 (Skill volatility is a central risk for low-income and vulnerable workers): ILO exposure measures and WEF's skill instability quantify the scale of transition pressures; unequal access to learning intensifies socio-economic insecurity.

R3 (Technical jobs are exposed through task re-bundling, not only displacement): AI changes task architecture inside technical roles, affecting entry-level pathways and wage structures; this is consistent with disruption signals in IT services.

R4 (India's distribution context is improving in consumption terms, but income pathways face AI transition risks): HCES indicates lower consumption inequality, yet labor-market segmentation and IT-model pressure imply that income and job-quality distribution may become more unequal without intervention.

9. Discussion

9.1 Why AI inequality is "capability inequality"

AI is not just a technology; it is a productivity regime requiring complements: skills, reliable connectivity, organizational adoption, and governance safeguards. Unequal access to these complements creates unequal ability to benefit from AI. OECD adoption evidence and UNDP/WTO divergence warnings jointly support this interpretation.

9.2 Retrenchment, restructuring, and responsible inference

Corporate restructuring in the tech sector signals organizational adaptation under efficiency and AI competition pressures. However, it is not methodologically valid to attribute layoffs to AI alone. This paper therefore uses restructuring evidence only to support the proposition that AI investment cycles often coincide with organizational redesign and shifting skill demand.

9.3 India's IT services: from labor-intensity to outcome-intensity

Reuters reporting suggests AI could pressure time-and-material billing models through reduced billable hours and faster delivery. If the revenue model shifts toward outcome-based pricing, firms may reduce demand for routine technical labor while increasing demand for high-skill, AI-augmented roles. This is a distribution-sensitive shift because IT jobs function as mobility channels for many households.

9.4 Reconciling "net job additions" with disruption

Nasscom's reporting indicates net employment growth and projections of expansion. This does not contradict disruption: a sector can grow while still restructuring internally. The distribution question is therefore who gets the new jobs and what happens to displaced or de-skilled roles.

10. Policy Recommendations

10.1 Learning equity as an equality policy:

Fund rapid, modular reskilling aligned to AI-augmented work. Provide stipends/time support for low-income learners. Measure training outcomes by wage mobility, not only enrollment.

10.2 Transition protections (income security during skill shocks)

Expand portable benefits and unemployment support linked to retraining pathways.
Prioritize mid-career workers in exposed occupations.

10.3 Accountable algorithmic management

Where algorithms allocate work, evaluate performance, or determine retention:
require explainability of earnings-affecting rules,provide accessible appeals and human review for high-impact decisions,mandate audits for disparate impacts on vulnerable groups.

10.4 India-specific: protect the entry-level technical ladder

Given AI's pressure on billable-hour models:
incentivize apprenticeship-style pathways and AI-assisted productivity training for early-career hires,support transitions into high-demand domains (data engineering, cybersecurity, AI assurance, cloud, domain solutions), align public skilling investments to verified industry transition roadmaps.

10.5 Distribution-sensitive AI metrics beyond GDP

Track: job quality (earnings stability, hours volatility), skill mobility outcomes, subgroup adoption/access to AI tools, sectoral wage polarization indicators. Use HCES + PLFS as continuing baselines and publish periodic "AI distribution dashboards."

10.6 International cooperation to prevent divergence

Support developing economies through: digital public infrastructure and broadband investment, compute access initiatives and capacity building, interoperable governance norms that reduce barriers to inclusive adoption.

11. Conclusion

Income and wealth inequalities caused due to policies , technological, knowledge , resources inequalities. AI's macroeconomic promise coexists with distributional risk. The strongest evidence-backed explanation is not that AI inevitably increases inequality, but that AI amplifies inequality where capabilities are unequal. Global institutional sources warn of divergence and highlight labor-market transformation; India's official indicators show robust growth and improving consumption inequality, yet structural labor segmentation and IT services model pressure create transition vulnerabilities. The policy objective should be shared gains, achieved through learning equity, transition protections, accountable algorithmic management, and distribution-sensitive monitoring. It demands urgent and inclusive dynamic policy to address potential widening of income and wealth inequalities.

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