Artificial Intelligence and labour market polarisation in India: Strategies for workforce reskilling

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Artificial Intelligence (AI), labour market polarisation, workforce reskilling, Emerging Economies

Abstract

Artificial Intelligence (AI) is transforming labour markets globally, creating high-skill opportunities while shrinking routine middle-skill jobs, intensifying inequality and urgent reskilling needs. This paper examines AI-driven labour market polarisation and workforce reskilling in India, where rapid technological change is reshaping job structures and skill demands. Grounded in Skill Biased Technological Change (SBTC) and Human Capital Theory, the study demonstrates that AI adoption disproportionately benefits high-skilled workers, driving growth in high-wage occupations, while routine middle-skilled roles decline, intensifying wage disparities and increasing demand for new competencies.

Using secondary data and official reports from 2020–2024, the analysis identifies India's distinctive polarisation pattern: a shrinking middle-skill workforce alongside a persistently large low skill labour segment. Limited reskilling coverage further constrains workers' ability to adapt to AI driven changes, risking a "low-skill trap." Comparative insights from the United Kingdom, a developed economy with more systematic AI adoption and structured training programs, highlight how proactive reskilling mitigates workforce displacement, offering lessons for emerging economies like India.

The findings underscore the urgent need for targeted workforce planning, investment in human capital, and collaboration between industry, government, and educational institutions. By linking theory with empirical evidence, this study provides actionable insights for policymakers, business leaders, and academics seeking to navigate AI-driven labour market transformations. The paper highlights how emerging economies can leverage AI for productivity and growth while addressing inequality and skill gaps, contributing to sustainable and inclusive workforce development.

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Introduction

Artificial Intelligence (AI) is now shaping almost every part of the economy. Like earlier breakthroughs such as electricity or the steam engine, it is changing how industries operate and how people work (Bresnahan & Trajtenberg, 1995). AI now handles many routine office and factory tasks while increasing demand for creative and analytical roles. This shift is changing both company operations and the structure of labour markets (Acemoglu, 2019). Researchers have long noted that every major wave of technology brings both progress and disruption — productivity rises, but many workers face displacement

Evidence from many countries shows a similar pattern: more high-skill and low-skill jobs, but fewer in the middle (Goos, 2014); (Autor, 2015). This phenomenon is explained by the Skill-Biased Technological Change (SBTC) framework, which highlights that technological progress disproportionately raises demand for skilled labour) (Autor, 2015) (Macias, 2016). However, outcomes differ across countries depending on institutions, policy support, and workforce adaptability (Siena et al., 2024).

In India, this issue is especially serious. Most of the country's huge workforce is in low-skill or informal jobs, and very few have access to proper training. Studies highlight India's "double vulnerability": high exposure to automatable middle-skill tasks and weak reskilling systems, which risk pushing displaced workers into the informal sector rather than into high-skill roles (Venkat Ram Reddy Ganuthula, 2025). Small and medium enterprises (SMEs) employ more than 110 million Indians but often struggle with costs, weak internet access, and limited knowledge of what AI can actually do for their business (Jadhav, 2021); (Bhalerao & Kumar, 2022). (Grace & Onum, 2022) add that without effective integration, SMEs will fail to capture productivity gains from AI adoption, widening the gap between advanced and traditional sectors.

Reskilling has become the most important policy tool for managing these changes. According to Human Capital Theory, investments in education and training enhance worker productivity and adaptability (Becker, 1993). International evidence shows that reskilling can mitigate displacement: McKinsey Global Institute estimates that over half of workers affected by automation could transition into new roles with proper retraining (Pablo Illanes, 2018). Yet in India, formal vocational training reaches only around 5% of the workforce, compared to 15–20% annually in advanced economies (Anon., 2022), Programmes such as Skill India and PMKVY are valuable foundations, but coverage remains limited and uneven, particularly for SMEs and rural workers.

Reskilling has become the most important policy tool for managing these changes Few studies provide a national-level framework linking these elements. This paper fills that gap by analysing India's labour trends from 2020 to 2024. It examines whether rising AI adoption could push the country into a low-skill trap, and what reskilling strategies might turn this disruption into a chance for more inclusive growth

Research Objectives

1. To analyse sectoral trends in AI adoption in India using secondary data (2020–2024).
2. To evaluate the extent and pattern of labour market polarisation across skill categories.
3. To assess the scale and coverage of workforce reskilling initiatives in India, with a focus on SMEs.
4. To propose targeted strategies for workforce reskilling that can ensure inclusive and sustainable growth.

Research Problem

Artificial Intelligence (AI) is transforming labour markets, but in India adoption is uneven. Large firms in IT, BFSI, and healthcare lead, while SMEs and traditional sectors lag due to financial and infrastructure gaps. This imbalance is driving labour market polarisation: high-skill jobs grow modestly, middle-skill jobs decline, and low-skill work remains dominant. With less than 5% of workers receiving formal training annually, displaced middle-skill workers risk sliding into informal, low-wage jobs. The core research problem is how India can design effective reskilling strategies to counter AI-driven polarisation and avoid a low-skill trap.

Research Gap

Most existing studies on AI and labour market transformation focus on developed countries such as the United States and the United Kingdom. Limited research has explored how these patterns appear in emerging economies like India, where the technology workforce and informal employment sectors differ significantly. There is also a lack of comparative studies that connect India's AI adoption trends with global frameworks such as Skill-Biased Technological Change (SBTC) and Human Capital Theory (HCT).

Significance Of The Study

This study provides a timely contribution by linking AI adoption with employment trends and reskilling efforts in India's growing digital economy. It helps policymakers, educators, and industry leaders understand where skill development investments are most needed. By comparing India's experience with that of the UK, the research also offers practical lessons for building inclusive, future ready workforce policies in emerging economies.

Research Question

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3. To assess the scale and coverage of workforce reskilling initiatives in India, with a focus on SMEs.
4. To propose targeted strategies for workforce reskilling that can ensure inclusive and sustainable growth.

Literature Review

This literature review synthesises three strands relevant to this study: (1) the economic role of AI and automation as general-purpose technologies, (2) labour-market polarisation and skill-biased technological change, and (3) workforce reskilling and human capital. The review highlights both consensus findings and unresolved questions, and it identifies the gap this paper addresses for India and SMEs.

AI And Automation

Researchers often compare AI to earlier breakthroughs like electricity or the steam engine because it touches almost every sector and changes how businesses work (Bresnahan & Trajtenberg, 1995). Studies show that AI tends to replace routine office or factory work but increases the value of creative and analytical skills (Autor, et al., 2003); (Acemoglu, 2019).This dual impact leads to uneven labour-market effects: productivity rises, but job displacement is concentrated in middle-skill roles.

In practice, whether a company can use AI well depends on simple but crucial factors — leadership support, good infrastructure, and whether workers are ready for change. (Jadhav, 2021) highlights that small and medium enterprises (SMEs) face particular barriers: limited financial resources, lack of technical expertise, and low awareness of AI applications. Similarly (Bhalerao & Kumar, 2022) note that SMEs struggle with both high costs and inadequate digital infrastructure. Despite these challenges, AI can improve efficiency, customer engagement, and decision-making when integrated effectively (Grace &

Onum, 2022). AI adoption is also heterogeneous across industries and regions (Ionașcu, 2025) finds that AI adoption depends on sectoral readiness, regulations, and institutional support. In advanced economies, strong policies and training systems drive faster adoption, while in developing countries it remains uneven and concentrated in sectors like IT and finance. In India, small and medium firms lag behind despite being major job providers.

Labour Market Polarisation and Skill-Biased Technological Change (SBTC)

Economists describe 'labour market polarisation' as what happens when technology cuts routine jobs but increases both high- and low-skill work (Goos, 2014).In the United States, (Autor & Dorn, 2013) show that the growth of computerisation and automation eroded clerical and administrative roles, while highskill professional jobs and low-skill service jobs expanded. Similar patterns are documented in the UK and Europe, where the "hollowing out" of middle-skill work is accompanied by rising wage inequality (Goos, 2014); (Macias, 2016).

This is explained through what economists call the Skill-Biased Technological Change (SBTC) theory. SBTC posits that new technologies disproportionately increase the productivity of highly skilled workers, raising their relative wages and widening income gaps (Autor, 2015). Studies show that automation and AI complement high-skill labour but substitute for routine tasks, thereby contributing directly to polarisation (Acemoglu, 2019); (Bessen, 2019)finds that firms implementing AI gained productivity benefits of 5–12% but saw a 3–6% decline in low-skill job share. However, technology alone does not determine polarisation. (Macias, 2016) emphasise the role of institutions, labour regulations, and organisational structures in shaping outcomes. This suggests that policy interventions can mitigate negative impacts of AI adoption.

For emerging economies such as India, the polarisation challenge is sharper. (Venkat Ram Reddy Ganuthula, 2025) Identifies India's "double vulnerability": a high share of low-skill workers and strong exposure of middle-skill jobs to automation, combined with limited reskilling systems. In countries like the UK, many displaced workers move up into new skilled roles. In India, however, many fall into informal, low-paid work instead — a pattern often described as a 'low-skill trap.

Workforce Reskilling and Human Capital Theory

Human Capital Theory argues that investments in education, skills, and training increase productivity and adaptability (Becker, 1993). Applied to AI, the theory highlights that workers with higher education and continuous training can transition into AI-complementary tasks, while those without are more vulnerable to displacement.

Global studies back this idea. For example, McKinsey estimates that automation could affect about 14% of jobs worldwide by 2030, but with retraining, many of those workers could move into new roles (Pablo Illanes, 2018). The (Anon., 2020) similarly projects that 40–50% of employees worldwide will require some form of retraining by 2030. Firms that invest in structured reskilling experience improved productivity and lower turnover, demonstrating the economic value of human capital investments.

In India, the skill gap is striking. The latest PLFS survey (2022–23) shows that fewer than 5% of workers have formal vocational training, and only about 15% have learned skills informally. Large-scale programmes such as the Skill India Mission and PMKVY aim to address these gaps, while private initiatives such as NASSCOM's Future Skills Prime focus on digital and AI-related skills. However, but most of these programmes focus on IT and banking. Traditional sectors and small businesses get very little support. (Anon., 2022) SMEs, despite employing more than 110 million workers, record reskilling penetration of only ~3%. This imbalance threatens to widen inequality as AI adoption accelerates. (Casilli & Posada, 2019) further note that platform work and digital labour intermediaries can expand access to training opportunities, though their benefits are uneven and depend on regulatory protections. Comparative insights from the UK highlight alternative approaches. Through the Apprenticeship Levy, National Skills Fund, and Lifelong Learning Entitlement, the UK reskills 15–20% of its workforce annually (Anon., 2023) Crucially, these programmes extend beyond digital-first industries, ensuring that sectors like healthcare, logistics, and manufacturing also benefit from workforce upgrading. These examples show that when government and industry work together, reskilling can reach more people and create fairer outcomes.

Conceptual Framework

Based on the reviewed literature and the study's objectives, the conceptual framework presented below illustrates the relationship between AI adoption, labour market polarisation, and workforce reskilling in India.

The conceptual framework links AI adoption, labour market polarisation, and workforce reskilling in India. It is based on a simple idea: technology creates new opportunities while also replacing routine work, and training determines how workers adapt. Since 2020, AI use has expanded quickly in IT, banking, and healthcare, but smaller firms and traditional sectors still lag. For example, banks use AI for fraud detection, yet many small manufacturers in Gujarat and Tamil Nadu struggle to afford or apply similar tools. This uneven adoption widens skill gaps—high-skill jobs rise while middle-skill roles decline.

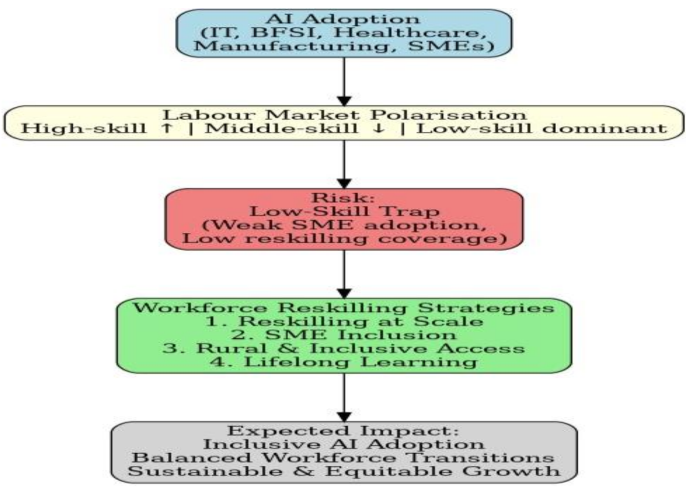

Figure 1: Conceptual Framework

The framework shows that expanding reskilling, especially for SMEs and rural workers, can act as a bridge to inclusive growth. Grounded in Human Capital Theory and Skill-Biased Technological Change (SBTC), it suggests that large-scale, continuous training can turn technological disruption into a chance for equitable development.

Research Methodology

This study uses a descriptive and comparative approach to examine how Artificial Intelligence (AI) is changing jobs, skills, and employment in India, with a brief comparison to the United Kingdom. It relies entirely on secondary data from reliable sources such as NASSCOM, World Economic Forum, PLFS, PwC, and the UK Office for National Statistics. Data on AI adoption, reskilling, and workforce trends were collected and organised into categories like adoption rate, skill levels, and sectoral changes, then presented through charts and tables. The analysis is guided by two key theories — Skill-Biased Technological Change (SBTC) and Human Capital Theory (HCT) which explain how technology affects skill demand and the role of training. The main limitation is that secondary sources use different timeframes and job categories, so the findings show overall trends rather than direct cause-and-effect relationships.

Data Analysis

This section analyses data from several national and international sources such as PLFS, CMIE, NASSCOM, ILO, and the World Bank. The goal is to understand how AI adoption has affected jobs and skill patterns in India between 2020 and 2024. The analysis is structured around three key dimensions: (i) AI adoption trends, (ii) employment distribution across skill categories (high-, middle-, and low-skill jobs), and (iii) the role of workforce reskilling initiatives.

AI Adoption Index in India (2020–2024)

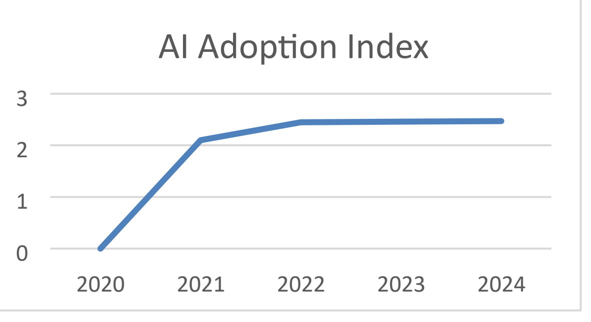

Figure 2:AI Adoption Index in India source: NASSCOM

The data show that India's AI adoption index increased from 1.8 in 2020 to 2.45 in 2022. Much of this rise came from rapid digitalisation during the pandemic. However, growth almost stopped after 2022, as large firms kept moving ahead while many smaller companies struggled with costs, skill shortages, and weak infrastructure. This trend has labour market effects: routine middle-skill jobs declined with automation, while demand grew for high-skill roles such as AI engineers, data analysts, and cloud specialists, deepening polarisation.

AI Adoption Index in India (UK Comparison)

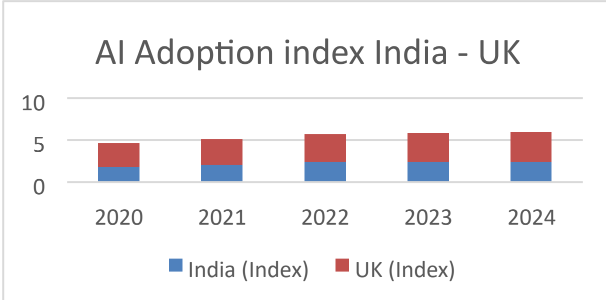

Figure 3:AI Adoption Index in India (UK Comparison)

Figure 3: compares India's AI adoption index with that of the UK between 2020 and 2024. The results highlight two key dynamics. First, India's index increased steadily from 1.8 in 2020 to 2.47 in 2024, confirming that adoption is advancing. However, growth slowed after 2022, suggesting that the initial momentum—driven largely by IT and BFSI—was not sustained across the wider economy. Second, India's adoption trajectory remains consistently below that of the UK, which reached 3.5 in 2024 (Anon., 2023). This difference mainly come from how each country support technology. In the UK, the government help small firm adopt AI through schemes and training hubs. In India, AI use in still centred in big cities and few advanced sectors such as IT and finance. The comparison underscores the narrow and uneven diffusion of AI in India. While the country is advancing, the plateau after 2022 indicates that without policy intervention—particularly to support SMEs and workforce training—AI adoption risks reinforcing inequality rather than driving inclusive growth.

Sector-Wise AI Adoption Rate For FY24 In India

Adoption here is defined as the share of firms in each sector using at least one AI-driven tool or process ((EY), 2021). Figure 5 shows a strongly uneven pattern in FY24: BFSI (68%), IT/software (60–65%), Pharma & Healthcare (52%), FMCG/Retail (43%), Manufacturing (28%), Infrastructure & Transport (20–22%), and Media & Entertainment (10–12%).

Table 1: Sector-Wise AI Adoption Rate

Sector	AI Adoption Rate (%)
Banking and Financial Services (BFSI)	68%
Technology	60-65%
Pharma and Healthcare	52%
FMCG and Retail	43%
Manufacturing	28%
Infrastructure & Transport	20-22%
Media & Entertainment	10-12%

Two findings stand out First, AI use is highest in sectors that already depend on data and technology, like banking and IT. Second, older industries such as manufacturing and transport still lag, even though they could gain a lot from automation.

By contrast, the UK shows a broader spread, with nearly 60% of SMEs using AI by 2023 (GOV.UK, 2023), compared to fewer than 25% in India. India's concentration in BFSI, IT, and healthcare contrasts with the UK's inclusive model, highlighting the risk that without SME support and wider adoption, AI benefits in India will remain narrow and reinforce labour market polarisation.

AI Adoption by Sector in India: 2019–2024 (%)

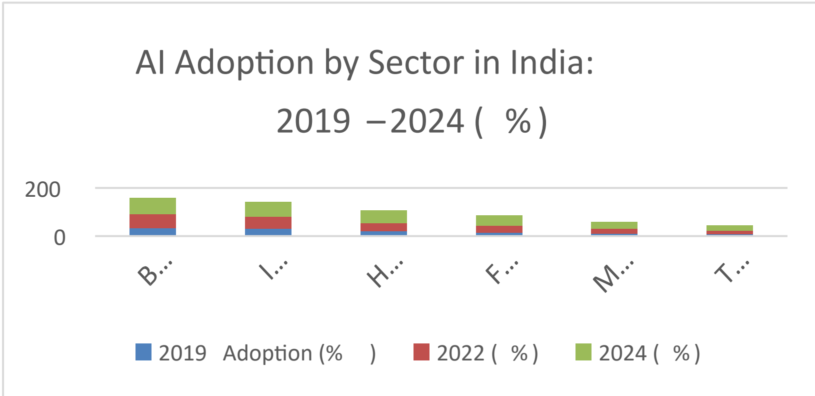

Figure 4: AI Adoption by Sector in India: 2019–2024 Source : (Anon., 2024), Author synthesis

Figure 4: illustrates how AI adoption in India's major sectors has grown from 2019 to 2024. The BFSI and IT/software industries lead the trend, increasing from under 40% to over 70%, driven by strong digital systems and uses such as fraud detection, algorithmic lending, and customer-service automation. Healthcare adoption also rose sharply, supported by telemedicine and digital diagnostics. In contrast, manufacturing and transport remain slow, reaching only around 30% due to high costs, outdated systems, and fragmented small firms. FMCG and retail show moderate growth, helped by e-commerce and supply chain analytics. Overall, India's AI growth is uneven — advanced, high-skill sectors are moving ahead faster than traditional, labour-intensive ones, increasing the risk of job polarisation.

AI Adoption Trends in India SMEs

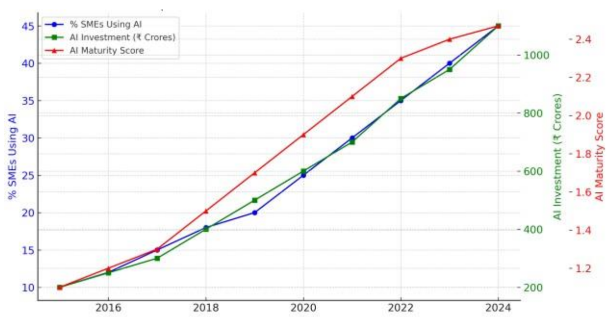

Figure 5 :AI adoption trends in India SMEs

This study explores how Artificial Intelligence (AI) is reshaping India's labour market. Between 2020 and 2024, AI use grew fast in IT, banking, and healthcare, but many traditional industries remain slow to adopt it. This uneven growth is widening skill gaps — high-skill jobs are increasing, middle-skill roles are shrinking, and low-skill work still dominates. Unlike the UK, which reskills 15–20% of its workforce each year through national programmes, India's training coverage remains limited. To avoid deeper inequality, India must expand large-scale reskilling, support SMEs, improve rural training access, and promote lifelong learning. With inclusive and practical skill policies, AI can become a driver of fair and sustainable growth.

Disaggregate by Firm Size (Large vs SMEs)

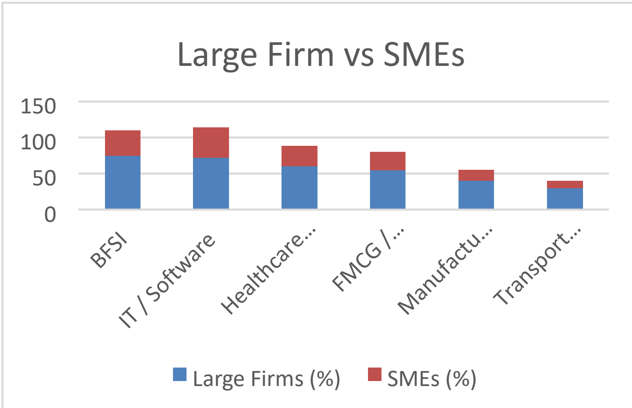

Figure 6 : Large Firm vs SMEs Source: Author synthesis

Figure 6 shows a clear gap between large firms and SMEs in AI adoption. Big companies are moving faster, while smaller firms are still experimenting or uncertain about its use. In BFSI and IT, over 70% of large firms use AI compared to only 30–40% of SMEs. Similar gaps appear in healthcare and retail, where adoption is led by large hospitals and e-commerce players. Manufacturing and transport remain lowest, with SMEs below 15% due to high costs and limited digital skills. Overall, AI adoption in India is concentrated in large firms, leaving SMEs behind despite employing most of the workforce.

India–UK SME Adoption Comparison

In India, SME AI adoption increased from 10% in 2015 to 45% in 2024, showing progress but still behind the UK, where over 60% of SMEs used AI by 2023. UK firms benefit from programmes like the AI Business Boost and Digital Catapult hubs that lower costs and support training. Indian SMEs, however, face financial limits and skill shortages, often stopping at pilot projects. This slows productivity and risks a low-skill trap. Targeted training and financial support are essential to make AI adoption in Indian SMEs more inclusive.

Labour Market Polarisation

Labour market polarisation refers to growing divergence in employment and wages specifically, an expansion of low-skill and high-skill jobs (or wage outcomes) with erosion of middle-skill/middle-wage jobs.

Table 2: Skill level

Skill Level	Typical Jobs	Share of Workforce (%)
High-Skill (Skill Levels 3 & 4)	IT professionals, engineers, managers, researchers	10–12%
Middle-Skill (Routine jobs)	Clerical staff, technicians, machine operators, supervisors	15–18%
Low-Skill (Skill Levels 1 & 2)	Agriculture labourers, retail assistants, drivers, domestic workers, construction	70–75%

Illustrates India's workforce distribution in 2023–24. Most workers (about 70–75%) remain in lowskill, low-paid jobs in sectors like agriculture and retail. Middle-skill roles (15–18%) are shrinking as automation replaces routine tasks, while high-skill jobs in IT, banking, and healthcare are rising due to growing demand. This U-shaped pattern—growth at the top, persistence at the bottom, and a shrinking middle—shows India's labour market becoming more divided without large-scale reskilling.

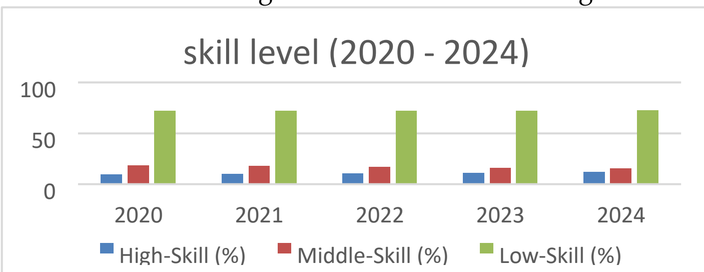

Figure 7: Skill Level (2020-2024)

Between 2020 and 2024, India's labour market became increasingly polarised. High-skill jobs rose from 9.5% to 12%, driven by AI adoption in IT, finance, and healthcare, but still involve only a small share of workers. Middle-skill roles declined from 18.5% to 15.5% as automation replaced clerical and technical tasks. This U-shaped trend mirrors global patterns: high-skill workers benefit from rising wages, while low-skill workers remain stuck in insecure jobs. Without large-scale reskilling, inequality will deepen and many workers may be excluded from AI-led growth.

Labour market polarisation (India - UK comparison)

India's 2024 workforce dominated by low-skill jobs (72.5%), with 15.5% in middle-skill and 12% in high-skill roles. This U-shaped trend reflects job polarisation, as many displaced workers shift to informal low-skill work. In contrast, the UK's labour market is more balanced, with 43% in high-skill roles. The comparison shows that strong reskilling can turn polarisation into upward mobility.

Workforce Reskilling

Artificial Intelligence (AI) and automation are rapidly changing India's job market, making workforce reskilling a top priority. While AI adoption is creating new demand for digital and analytical skills, the readiness of India's workforce remains low. National studies suggest that 40–50% of workers will need reskilling by 2030 to stay employable, yet only about 4.7% have formal vocational training and around 14–

15% have informal training (PLFS, 2022–23). This shows a major gap between the skills workers have and the skills the AI-driven economy requires.

Workforce Reskilling in India (2020–2024)

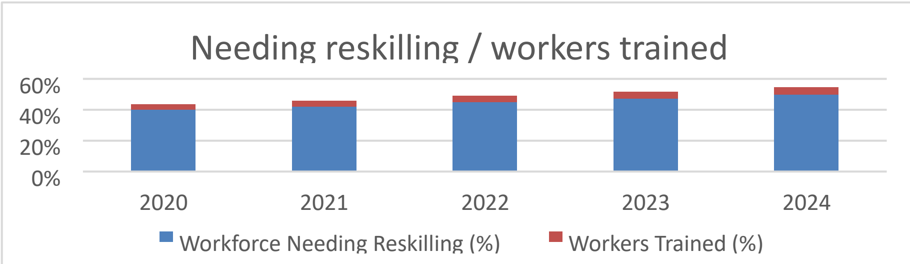

Figure 8 : workforce Reskilling /Trained

Figure 8: illustrates a gradual rise in India's reskilled workforce, from 3.5% in 2020 to 4.7% in 2024. However, this progress is slow compared to the growing need, with 40–50% of workers requiring new skills by 2030. The widening gap shows India is not keeping pace with technological change. In contrast, the UK reskills about 15–20% of its workforce each year through coordinated national programmes, proving that structured policy efforts are essential to prevent large-scale job exclusion.

Reskilling Coverage by Sector in India (2020–2024, % of sectoral workforce trained annually)

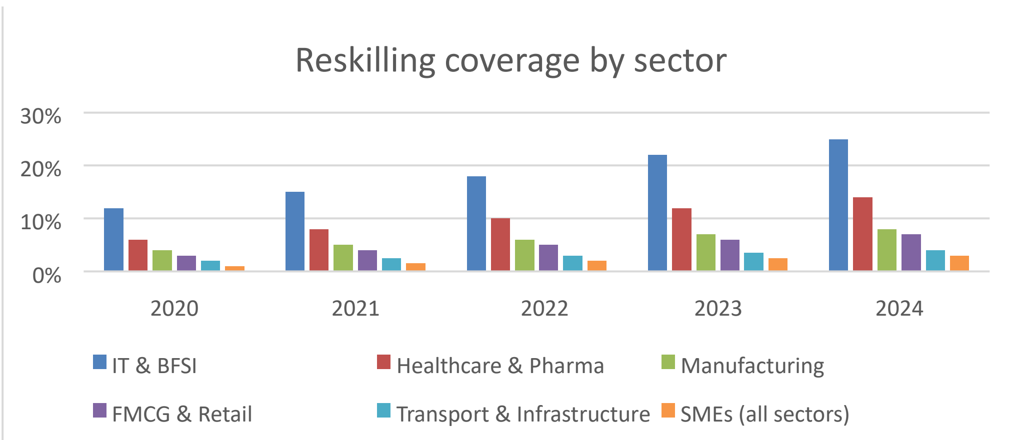

Figure 9 :Reskilling Coverage by Sector

Figure 9: illustrates major differences in reskilling across Indian sectors from 2020 to 2024. IT and BFSI lead, rising from 12% to 25%, supported by strong digital infrastructure and investment. Healthcare and Pharma improved from 6% to 14% due to growth in telemedicine and digital diagnostics. In contrast, manufacturing, FMCG/retail, and transport/infrastructure show slow progress (4–8%), while SMEs remain lowest at 1–3%. This uneven progress shows reskilling is concentrated in high-tech sectors, leaving

traditional industries behind. Without wider, targeted training efforts, AI could deepen inequality by excluding middle- and low-skill workers.

AI Adoption and Reskilling Penetration by Sector in India (2024)

The figure shows that while AI adoption is growing across sectors, training is lagging behind. BFSI and IT lead with 12–15% of workers trained, but most employees remain unprepared. Healthcare and retail have only 5–7% coverage, while manufacturing and transport are below 3%, putting workers at risk of being left behind. Overall, reskilling is not keeping pace with adoption, leaving large parts of the workforce vulnerable.

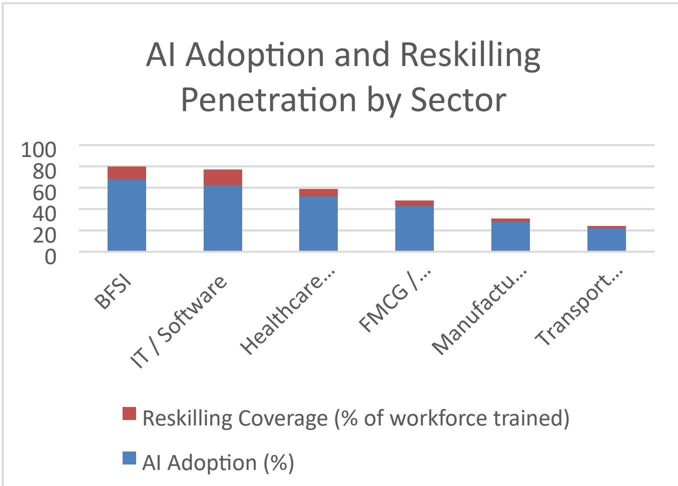

Figure 10 : AI adoption and reskilling coverage Source: Author synthesis

Workforce Reskilling India – UK comparison

In India, initiatives such as Skill India Mission, PMKVY, and NSDC have trained millions, but still reach less than 5% of the workforce each year. IT and BFSI sectors lead through NASSCOM's Future Skills Prime, while SMEs and traditional industries lag at around 3% due to financial and institutional barriers. Digital training platforms are growing, but overall efforts remain scattered. In contrast, the UK reskills 15–20% of its workforce annually through coordinated national programmes and strong SME support. India needs similar large-scale, inclusive reskilling to reduce inequality and build an AI-ready workforce.

Discussion

The findings show that Artificial Intelligence (AI) is reshaping India's labour market, with rapid adoption in IT, finance, and telecom, while manufacturing and small firms lag behind. This uneven growth is creating job polarisation — rising demand for high-skilled professionals and fewer routine or mid-skill roles. The results align with Skill-Biased Technological Change (SBTC), which explains how technology favours skilled labour, and Human Capital Theory (HCT), which stresses the value of training and education.

Compared with the UK, India's reskilling efforts are still evolving. The UK's national programmes link education with digital skill needs, while India's initiatives like Skill India and NASSCOM Future

Skills need stronger coordination. AI can raise productivity and create new jobs, but without widespread training, it could deepen inequality.

Overall, India is progressing but must expand digital reskilling and policy support to ensure AI drives inclusive, balanced, and sustainable growth rather than widening workforce divides.

Conclusion and Policy Recommendations

This study examines how Artificial Intelligence (AI) is reshaping India's labour market. Between 2020 and 2024, AI use grew rapidly in IT, banking, and healthcare, while small and traditional industries lagged behind. As a result, India's job market is becoming more uneven — high-skill jobs are increasing, middle-skill jobs are shrinking, and low-skill work still dominates, creating a risk of long-term inequality. Compared with the United Kingdom, which reskills 15–20% of its workforce annually through national programmes, India's training coverage remains limited and fragmented.

To address these challenges, India should focus on four key areas. First, expand national programmes like Skill India and PMKVY to reskill at least 10–15% of workers each year. Second, support SMEs through incentives and digital training hubs. Third, improve rural access by offering local language e-learning and mobile training for informal workers. Finally, promote lifelong learning to help employees continuously upgrade their skills. With coordinated action, India can turn AI-driven change into a path for inclusive and sustainable growth.

However, this study is limited to secondary data, which may not fully capture recent on-ground training outcomes or firm-level variations.

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