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AI, Automation and India's Workforce

Who Gains, Who's Exposed, and How Policy Can Shape the Future

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The views expressed are personal and do not represent the authors' institutions.

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This paper is intended for discussion within policy circles, industry practitioners, and among national and multilateral organisations working on the impact of artificial intelligence on employment and the labour market in India and other countries. The presentation prioritises accessibility for a policy audience without compromising analytical rigour.

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Foreword

The Economic Survey 2025-26 devoted a chapter to the evolution of India's AI ecosystem, tracing the build-out of compute, infrastructure, models and applications across the economy. What that chapter could not do, within its scope at that time, was follow AI down to the level of individual occupations and ask which of India's workers stand to gain from it and which face displacement. This paper does exactly that, using two rounds of labour force survey data to track how India's occupational structure has shifted in relation to AI exposure, complementarity and routine task content since 2012.

The central finding is noteworthy: The share of India's workforce in AI-exposed occupations has risen modestly since 2012 and is now close to a quarter. The composition within that exposed workforce has moved in the right direction: the share where AI is likely to raise productivity has risen to nearly 31 per cent. Yet AI-substitution-pressure work still outweighs complementary work by roughly one and a half to one. In this context, the task before policymakers is to improve the quality of existing exposure through AI literacy, task redesign and reskilling, specifically aimed at occupations where the balance between augmentation and substitution remains uncertain.

A second, and for India larger, transition runs alongside this one. Employment in high-routine occupations, susceptible to conventional automation and mechanisation regardless of what happens with AI, has risen by 4.8 percentage points since 2012. This shift predates generative AI and will continue independently of it, which means the window to build reskilling capacity is open now, before disruption becomes visible in employment statistics.

The paper's treatment of India's shortage sectors, health, elderly care, education and the skilled trades, is particularly useful for policy design. These are precisely the non-routine, high-complementarity occupations, which are also human-centric, where India needs more workers and where the workforce is currently not moving. Turning them into a genuine absorption channel will require credential parity, portable social protection and financing that follows workers rather than employers.

Similarly, the gender findings are equally interesting: women's AI-exposed employment is of distinctly higher quality than men's. Participation, not technological exposure, is the constraint, and the policy recommendation follows directly: childcare, safe transport and safe housing belong in labour-market policy rather than in a separate welfare column. The state-level analysis, showing that the poorest large states face both lower exposure and a weaker mix of the exposure they do have, serves as a handy reminder that AI's employment effects will not automatically resolve India's older regional disparities. A well-sequenced policy response, along with an AI policy, will be necessary to help narrow them.

Dr. V. Anantha Nageswaran

Chief Economic Adviser to the Government of India

Executive Summary

At a Glance

Much of the debate on Artificial Intelligence (AI) and jobs is framed either as promise or threat, with little evidence specific to India. For business leaders and policymakers, the practical questions are: how much of India's workforce is in occupations where AI and conventional automation can perform a significant share of the work? In which of these jobs is AI more likely to complement workers and raise productivity, and in which does it create substitution pressure? And what can firms and policymakers do to shape how AI and automation affect jobs and workers?

We address the first question using an occupation-level measure of AI exposure: the degree to which an occupation's tasks overlap with what AI can do. For the second, we use AI complementarity, which captures whether job task profiles make AI more likely to augment workers. A third measure, routine task intensity, captures broader exposure to automation.

Applying these measures to national worker-level data for 2012 and 2025, we find that India currently has about 46 million workers who can gain from AI through productivity increases, assuming they have foundational skills and domain expertise. Productivity gains in complementary occupations are likely to generate positive spillovers through backward and forward linkages, an effect this paper does not assess. The upside to AI complementarity is in urban, prime-age workers and, encouragingly, female-led occupations.

Nearly 197 million workers are in occupations where a high share of tasks could be automated, though the shift is likely to be gradual. The risk is concentrated among entry-level workers: 39.4 per cent of under-25s are in high-routine jobs, the highest of any cohort. In some services, especially those delivered by a single individual, automation will not completely replace the owner-worker.

This paper's analysis of employed people underestimates job risk among young people. In 2025, based on the Periodic Labour Force Survey 2025, we find that over 20 million Indians aged 15–64 were unemployed, including 18.7 million aged 15–34. The graduate unemployment rate among young adults (20–29 years) is more than twice the overall rate; among those with engineering degrees, 25 per cent were unemployed¹. Moreover, these figures understate the problem because about half of people in their 20s do not look for paid work and are therefore not counted as unemployed.

The aggregate employment effects of AI and automation – positive or negative – will take time to show, with adoption uneven across firms and sectors: deployment costs need to fall, complementary human skills need to

46 million

can gain from AI; depends on foundational skills and domain expertise

39.4%

of employed under-25s in high-routine jobs; a higher automation risk

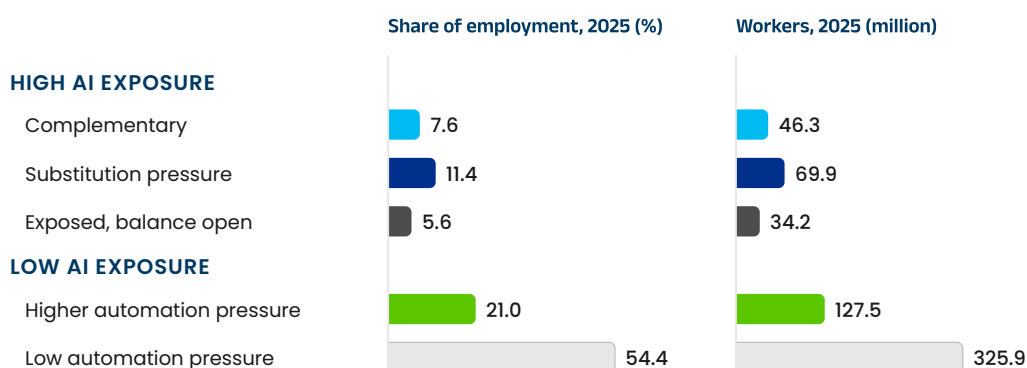
Prioritise Youth

High graduate unemployment when about half in their 20s seek jobs

¹ Mahambare and Alam (2026), "Elusive jobs: how AI will demand even greater patience of India's unemployed youth", Mint, 11 May

improve, machines need to become more capable and reliable, and firms need to work out where and how to deploy them. Prudence, however, calls for acting early rather than waiting.

Employment across job regimes, 2025



Note: Workers aged 15–64. Share of total employment (per cent); workers (million), estimated as population × work participation rate × regime share by age and sex.

Source: Authors' calculations.

The Good News:

- **The share of workers employed in high Artificial Intelligence (AI) exposure occupations in India has risen modestly:** from 21.1 per cent in 2012² to 24.6 per cent in 2025 among 15- to 64-year-olds. Exposure is measured against AI capabilities applied to the occupational structure of 2012 and 2025³.
- **The quality of AI exposure has improved from a low base:** The share of employment in AI-complementary occupations – where AI is more likely to raise labour productivity than substitute for the worker – rose from 5.3 per cent in 2012 to 7.6 per cent in 2025. That is, **46 million⁴ workers can gain from AI-induced productivity gains.**
- **AI-complementary work is more common in urban areas** – 15.8 per cent in urban India vs 4.3 per cent in rural India. About one in six urban workers is in an AI-complementary job.
- **Of the five job regimes, the AI-complementary one has the smallest gender gap:** 7.7 per cent of employed men and 7.4 per cent of employed women work in it. Because far fewer women are employed, however, men outnumber women in these jobs by about two to one (31.6 million against 14.8 million).

² Based on data from the Employment and Unemployment Survey of 2011–12

³ AI exposure is measured using today's AI capabilities, applied to each year's occupational mix, so '2012 exposure' shows how much of that year's workforce was already in AI-susceptible occupations, judged by current technology. The data points quoted in this section are for 2025 except those specifically compared with 2012

⁴ Absolute numbers are estimated as population × work participation rate × regime share for each age–sex group and summed; they may differ slightly from the 15–64 percentages, which are direct survey-weighted estimates.

- **Women lead men in urban India in terms of share of AI-complementary work** – 19.5 per cent of women employed in urban areas vs 14.5 per cent of urban men. Among women, AI-exposed employment is of better quality than men's, reflecting concentration in non-routine health and education work.
- **Maharashtra, Haryana, Kerala and Tamil Nadu** have the highest shares of workers in AI-complementary occupations to build on.

The Hard News:

- **A broader shift, which began before AI, is also underway** – Nearly 1 in 3 of the employed work in occupations where the share of routine tasks is relatively high, including both those who have high and low exposure to AI. The share of jobs with relatively high-routine tasks in total employment rose from 27.6 per cent in 2012 to 32.4 per cent in 2025. This share likely overstates the actual risk of job loss: in some services, especially those run by a single owner-worker, automation may take over routine tasks without replacing the worker.
- **The share of high-routine occupations is higher in the younger and urban cohort** – This share is 39.4 per cent (15–24 age group), falling to 29 per cent (45–54) and 24.2 per cent (55–64). In urban areas, 55.0 per cent of 15–24-year-olds are in high-routine work, combining high and low AI exposure. Youth have the worst high-routine-to-complementary ratio by a wide margin – 7.6:1 at 15–24, against roughly 4:1 for every older cohort. About 47 per cent of urban workers are in high-routine work. The task is to keep improving exposure quality, not to slow the technology.
- **Rural India is insulated, not advantaged:** Among rural workers, 26.5 per cent are in high-routine jobs, and only 4.3 per cent are in AI-complementary occupations. 66.3 per cent are in low AI-exposure, low-routine jobs, mostly farming. There is no near-term AI-related disruption, but there is a risk of farm mechanisation. Rural women are the furthest out: 4.1 per cent complementary, 73.8 per cent low-exposure/low-routine.
- Populous low-income states (**Uttar Pradesh, Bihar, Jharkhand, Madhya Pradesh**) face a double disadvantage: both less exposure and a lower-quality mix of the exposure.

On the Fence

- **In 2025, around 34.2 million workers (5.6 per cent of those aged 15–64) were in occupations** – Information technology, business services, and personal services professionals among them – where AI will take over some tasks but a skilled professional is still needed to do the job, at least for now. This will also be the case in some occupations classified as high-routine occupations.
- **Karnataka and Telangana have high exposure but a complementary share** below the national average, largely because many of their exposed workers are in jobs where AI could either augment or replace tasks depending on how work is redesigned.

Policy Suggestions

- **Help the AI-complementary workforce and firms make the most of AI.** Build AI fluency and domain expertise among workers so that they can gain from higher value-added work and new roles such as forward-deployed engineers, AI validation, research and development, including clinical trials, and AI strategy in information technology, Global Capability Centres, pharmaceuticals and high-skilled manufacturing. Productivity gains in these sectors could spill over positively to other sectors through backward and forward linkages.
- **Encourage AI start-ups and consultancy firms to help industry overcome AI bottlenecks;** encourage industry organisations to start an AI-advisory helpline for small and medium enterprises, the self-employed and the public sector. Failing this, large firms will pull ahead of smaller ones in productivity.
- **Facilitate the growth of heavily regulated AI-infrastructure sectors** – Sectors such as energy, water, submarine cables and data-transfer repair capacity, which support the development and spread of AI, are heavily regulated by government. Developing these sectors will enable wide-spread access, improve reliability, and keep utility prices affordable for businesses and families.
- **Reskill exposed workers before losses materialise** – Prioritise young, urban labour-market entrants, the unemployed and those in routine clerical, back-office and low-discretion technical roles for training in judgement, verification, and client engagement; redesign workflows from routine execution to oversight and exception-handling; and target new AI-induced jobs such as data annotators and AI trainers, though some may be temporary.
- **Support the reinstatement channel in the data economy** – Publish a model contract and minimum standards for labelling, annotation and similar platform work, and bring these workers within portable social protection; create progression pathways from routine digital tasks to AI evaluation and expert validation, with credentials, verified experience and platform ratings that workers can carry across platforms; and treat expert-generated training data in medicine, law, engineering and Indic languages as a skilled services export.
- **Refine skill training and improve access to high-quality AI tools** – Keep training modular, with stipends linked to completion, and redesign curricula across the National Skills Qualifications Framework, industrial training institutes (ITIs), polytechnics, engineering and commerce to build domain knowledge, communication and judgement rather than simply familiarity with AI tools. Because frontier AI tools increasingly require paid subscriptions and are largely designed for English-speaking, digitally skilled users, access to high-quality AI will otherwise be sharply unequal.
- **Turn the shortage sectors into an absorption channel.** Create an internationally recognised credential tier, equivalent to a degree, for nursing,

elderly care and childcare, and the skilled trades, ensuring the upgrading of ITIs and teacher-training colleges before running a recognition campaign. Develop entrepreneurial skills among young people and ease credit, regulatory requirements and platform matching for the self-employed. Target the low income populous states, with jobs in sectors such as agro-processing. Consider facilitating outward migration in occupations where labour shortages are acute in other countries.

- **Start early and make AI literacy near-universal.** Set a minimum requirement for AI practice from middle school, and create a single, subsidised AI entitlement for adults – a credit for tools and training, scaled by income – delivered through Skill India Digital Hub with assisted enrolment at Common Service Centres and ITIs, and co-funded through corporate social responsibility contributions of the private corporate sector.
- **Raise learning and completion together.** Build logical thinking, problem solving, articulation, negotiation, adaptability and the ability to deal with uncertainty from the early grades; set a minimum share for these skills in NSQF-aligned courses; include an industry-supervised capstone in AICTE-approved engineering programmes; add judgement-intensive task modules with supervised workplace exposure to apprenticeships; and allow subject combinations across streams, with more oral and practical assessment.
- **Reorganise social protection.** Link benefits to the individual worker as they move between platforms, employers, states and self-employment, enrol workers automatically with the option to opt out, and give workers leaving routine occupations temporary transition support.
- **Restructure labour subsidy.** Redirect wage and hiring subsidies, including skilling subsidies, from payroll payments towards AI-complementary training and towards occupations with long-term potential such as health, care and education, tapering support where automation risk is material.
- **Treat housing and commuting as labour-market infrastructure.** Shift housing support towards affordable urban rental, encourage the building of affordable urban housing, nudge states to adopt model tenancy legislation, and prioritise bus fleets and frequency for intra-city travel. Without affordable access to homes and quality transport, the young are more disadvantaged.
- **Build on women's position in complementary work.** Treat childcare near or in schools, elderly care infrastructure, safe transport and, for single women, affordable and safe urban housing, including working women's hostels, as labour-market policy; create pathways into health, care and teaching jobs; support women returning to work after career breaks.
- **Build continuous measurement.** Combine PLFS occupational data with National Career Service vacancies, e-Shram data and online job postings to track changes in occupational demand and skills early enough for education and skilling policy to respond.

1. Introduction



A country's prosperity ultimately rests on two things: how many people participate in the labour market, and how productively they work. In this context, the arrival of generative AI has revived familiar questions: Will technology and automation displace more jobs than they create? Which workers will benefit from technology raising their productivity? How can we prepare workers for new technologies?

For India, Artificial Intelligence (AI) has arrived at a time when the country faces several labour market challenges. While the headline unemployment rate of about 3.2 per cent for 2024 (MoSPI, 2025) appears low, it significantly understates India's jobs problem. In 2024, about half of India's young adults (20-29 years) were employed (Mahambare et al., 2026a). First, unemployment is measured against the labour force – working-age people who are working or seeking work – which is artificially small because the majority of women do not seek paid work and higher education enrolment has lowered the number of people in their early twenties looking for paid work. Second, as education levels have risen, unemployment among graduates in their twenties has climbed into double digits, more than twice the aggregate (Mahambare and Alam, 2026). Third, young people appear to hold out for higher-quality jobs before eventually settling for whatever is available since unemployment among young men vanishes by their late twenties (Mahambare et al., 2021).

At the same time, labour shortages are acute in several occupations including trade skills (NITI Aayog, 2023) and healthcare. For example,

India is estimated to need some 1.8 million additional doctors, nurses and midwives by 2030 to reach the WHO minimum threshold of 44.5 health workers per 10,000 population (Karan et al., 2021). The education sector has teacher vacancies across school and higher education systems (UDISE+, 2025), as do the skilled trades such as plumbers and electricians. Elderly care is an emerging and largely unmeasured area of demand as the population ages (UNFPA and IIPS, 2023), where demand is likely to grow further as AI accelerates drug development and improves disease control, extending longevity. In science and engineering, employability remains constrained by a mismatch between graduate preparation and industry requirements, particularly in problem-solving, adaptability, teamwork, project management and the use of modern technological tools (Gope and Gope, 2022).

In short, the mismatch is qualitative – a misalignment of skills, location and expectations – rather than a simple shortfall in terms of the number of jobs. New technologies that reshape the content of work will interact with these existing labour market pressures. For example, in sectors such as textiles, where labour turnover is high, automation can ease persistent shortages. In others, such as entry-level IT work, AI may substitute for workers: demand for basic coding, bug-fixing and routine maintenance falls, while work built on physical presence and human interaction remains comparatively insulated (Mahambare, 2023a). Elsewhere, it will raise labour productivity and,

with it, wages, and in some cases generate entirely new categories of work.

Much of the literature attributes the decline in the labour share across advanced economies partly to automation, which lets firms produce the same output with less labour (Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2022, p. 1975; Hubmer and Restrepo, 2026). Firm-level evidence is more mixed. Using administrative data on French firms for 1994–2019, Bárány, Patel and Siegel (2026a) find that firms that automated more did not see larger falls in their labour share. They suggest that automation may instead create demand for workers who design and maintain more complex systems, or raise the value of the tasks that remain (Bárány, Patel and Siegel, 2026b).

Against this background, this paper asks whether, between 2011–12 (2012 hereafter) and 2025, India's workforce has moved towards or away from occupations whose task content carries technological exposure, complementarity, and susceptibility to automation arising from the repetitive nature of the work. It also asks whether employment movement differs across rural and urban labour markets, men and women, the employment life cycle, and states. Based on the emerging employment picture, we then suggest policy steps to enhance India's readiness to take advantage of the AI revolution, raise labour productivity, and provide job opportunities in sectors where AI and automation will be slow to invade.

2. Methodology

We follow a two-step methodology. First, following existing studies, we classify occupations into groups based on three parameters: exposure to AI, whether AI is likely to act as a complement that raises human productivity rather than a substitute, and the scope for task automation within the occupation (routine task intensity). Second, we identify the share of India's workforce in each occupation regime and aggregate it to provide an overall picture of exposure. Appendix A6 compares the AI exposure index used here with alternative measures and explains the choice of index.

We combine employment microdata from India's two labour-force surveys – the Employment and Unemployment Survey for 2011–12 (2012) and the Periodic Labour Force Survey 2025 – to create a common unit-level database and harmonise the two rounds on occupational classification, employment status, and major demographic characteristics. Because the two surveys differ in design, comparisons between them are interpreted as broad structural movements rather than precise year-on-year changes. The analysis is

restricted to individuals identified as employed on the usual status (principal plus subsidiary) basis and therefore includes the self-employed and unpaid family workers alongside regular wage and casual workers. Occupational classifications are harmonised across survey rounds by mapping National Classification of Occupations (NCO) 2004 occupations to the NCO-2015 structure at the three-digit level using the official concordance. The harmonised occupations are subsequently linked at the two-digit level to the occupation-level technological measures used in the analysis. The Appendix provides methodological details. Because the two classifications record small business owners differently, self-employed workers coded in managerial occupations in 2011–12 are assigned the occupation corresponding to their industry of work, consistent with PLFS 2025 coding practice (Appendix).

Classification of Occupations

The occupation-level measures of AI exposure, AI complementarity and routine task intensity used in the analysis are taken from the

accompanying occupational data to Arias et al. (2025). This analysis draws on the methodological frameworks of Felten, Raj and Seamans (2021), Pizzinelli et al. (2023), and Autor and Dorn (2013), respectively. The occupation-level indices are used as reported rather than independently reconstructed from the underlying task data.

AI Exposure

AI exposure, following Felten, Raj and Seamans (2021), measures the degree to which an occupation's tasks overlap with what AI can do. The exposure score is standardised, so an occupation scoring above zero is classified as AI-exposed, meaning above-average overlap in the reference distribution. This does not by itself indicate whether AI will substitute for workers or augment their productivity; that depends partly on AI complementarity.

One property of the measure deserves emphasis at the outset: exposure is dynamic, not fixed. Eloundou et al. (2024) find that a large language model on its own allows roughly 15 per cent of worker tasks to be completed substantially faster at the same quality, but that this rises to between 47 and 56 per cent once software and tooling built on top of the model are taken into account. As AI capabilities and complementary software evolve, these exposure measures should therefore be interpreted as reflecting technological exposure at a particular stage of technological development rather than as immutable occupational characteristics.

AI Complementarity

AI complementarity, following Pizzinelli et al. (2023), captures whether the nature of the work – the judgement, responsibility, communication, or discretion it demands – makes AI more likely to augment a worker's output than to substitute for her entirely; higher values indicate greater complementarity. Among AI-exposed occupations, we classify those with complementarity scores above the employment-weighted occupation mean across occupations in 2025 as high-complementarity,

and those at or below it as low-complementarity. Weighting by 2025 employment anchors the threshold to India's current occupational structure, and we hold it fixed across both survey rounds. This dimension separates two occupations with identical exposure scores into different labour-market outcomes: one in which AI is more likely to augment work and potentially raise earnings, and one in which AI may substitute for humans in a relatively high proportion of tasks. We also calculate the substitution-to-complementary ratio, defined as employment in the substitution-pressure regime divided by employment in the complementary regime: a value above 1.0 indicates that employment in the substitution-pressure regime exceeds employment in the complementary regime.

Routine Task Intensity

An occupation can have low AI exposure today and still be highly vulnerable – not to AI, but to conventional automation. Routine task intensity (RTI), following the task-based approach of Autor and Dorn (2013), captures this by measuring how much an occupation consists of explicit, repetitive, codifiable tasks. High-RTI occupations – whether or not AI touches them – are the ones most exposed to being mechanised. An occupation is classified as high-routine when its RTI score is greater than zero (see Appendix).

The Occupation Regimes

Based on the above three measures, India's employment is grouped by occupation into five regimes (Table 1): 1) non-routine work with high exposure to AI, which is highly complementary to human labour, where AI is most likely to augment work, with potential productivity and earnings gains; 2) AI-exposed occupations with low complementarity and high routine content, where substitution pressure and job losses are strongest; 3) AI-exposed occupations with low complementarity and low routine content, where the balance between augmentation and substitution is still open; 4) occupations with low AI exposure but high routine content, insulated from AI yet exposed to conventional

automation; and 5) occupations with low AI exposure and low routine content, largely insu-

lated from both, spanning a wide range of occupations from professional to subsistence.

Table 1: Occupation Regimes

Regime	AI exposure	AI Complementarity	Routine Task Intensity	Interpretation
1	High	High	Low	AI-exposed, complementary, non-routine - AI augments; potential gain in productivity and earnings
2	High	Low	High	AI-exposed, low-complementarity, routine - AI and automation substitution pressure
3	High	Low	Low	AI-exposed, low-complementarity, non-routine - augmentation-substitution balance unresolved; most responsive to task redesign
4	Low	Not applicable	High	Low AI exposure, high routine - insulated from AI, exposed to conventional automation. The pace of automation depends on India's factor prices
5	Low	Not applicable	Low	Low AI exposure, non-routine - insulated from both AI and task-based automation; spans skilled and unskilled work

Note: No occupation falls under the high AI exposure, high complementarity and high routine category.

Source: Authors' explanations

Table 2: Occupation Classification into Regimes

High AI Exposure Occupations			Low AI Exposure Occupations	
High AI complementary-Low routine	Low AI complementarity-High routine	Low AI complementarity-Low routine	High routine	Low routine
Health Professionals and Associates	General and Keyboard Clerks	ICT Professionals and Technicians	Food Preparation Assistants	Farm and primary sector occupations
Science and Engineering Professionals	Other Clerical Support Workers	Business and Administration Professionals	Handicraft and Printing Workers	Drivers and Mobile Plant Operators
Legal, Social and Cultural Professionals	Numerical and Material Recording Clerks	Business and Administration Associates	Cleaners and Helpers	Metal, Machinery and Related Trades Workers
Administrative, Commercial, Production and Service Managers	Sales Workers	Personal Service Workers	Assemblers, Stationary Plant and Machine Operators	Building and Related Trades Workers
Hospitality, Retail and Other Services Managers	Customer Services Clerks	Personal Care Workers	Food Processing, Garment and Related Trades Workers	Science and Engineering Associates
Teaching Professionals		Legal, Social, Cultural and Related Associates	Refuse Workers and Other Elementary Workers	Electrical and Electronics Trades Workers
Chief Executives, Senior Officials and Legislators			Construction and Manufacturing Labourers	Protective Services Workers

Source: Authors' explanations

The three occupational attributes – AI exposure, AI complementarity, and RTI – are held fixed over time and are taken from the relevant published work. What moves is the distribution of Indian workers across occupations. So when we say a specific job regime’s employment share rose between 2012 and 2025, we mean workers shifted into occupations that are, by today’s technological standards, more exposed to AI. We note one caveat: all three

indices are built from task descriptions of US occupations and are applied here on the assumption that task content within an occupational category transfers reasonably well. Because the indices are attached at the two-digit level, every worker in a two-digit group carries the same scores, so movements within occupational groups – for example from informal to formal retail – are not captured.



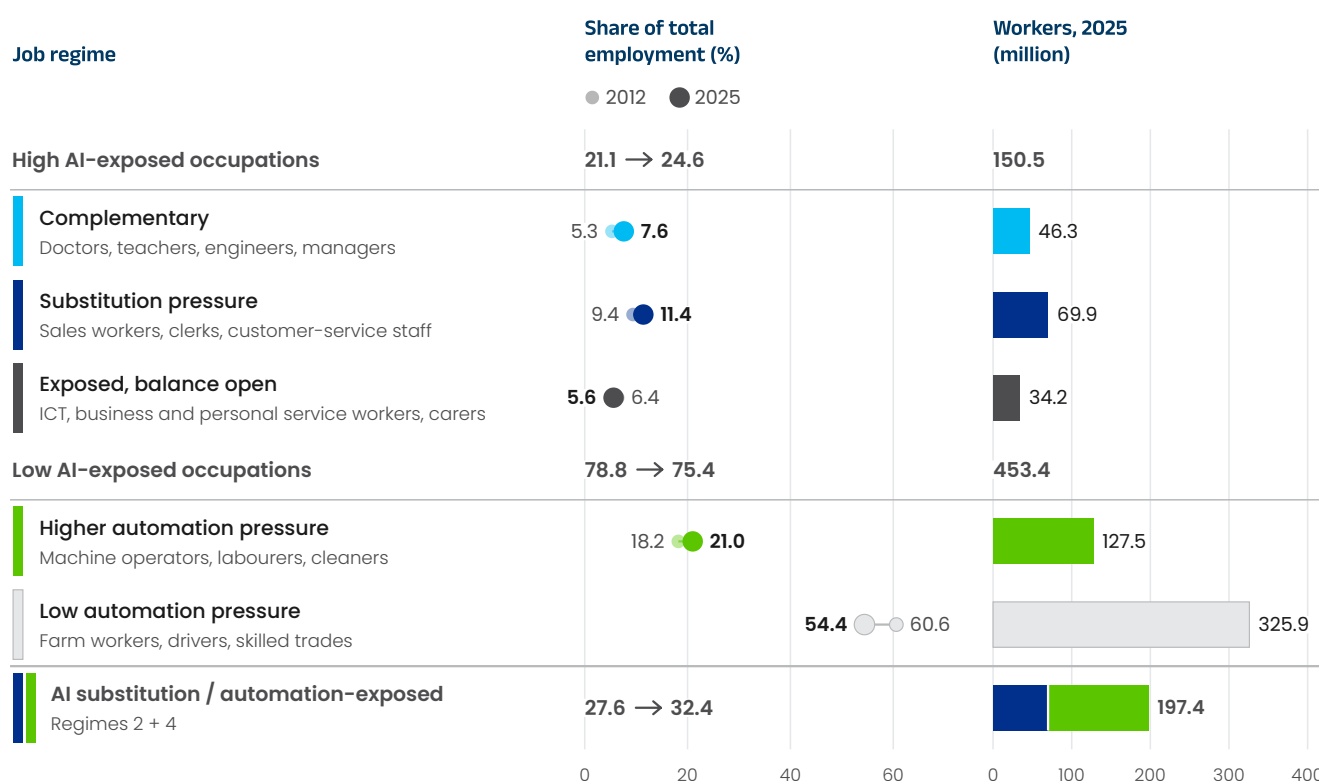
3. Findings

3.1 Aggregate Employment Shares across Technological Regimes

- We find that in 2025, about a quarter of Indian employment (15–64 age group) was in occupations exposed to AI (Figure 1). About 7.6 per cent of all employment (~46.3

million), an improvement of 2.3 percentage points over 2012, was in occupations where the appropriate use of AI is likely to raise productivity – health and teaching professionals, scientists and engineers, and managers – and this is the base from which India’s augmentable workforce can grow.

Figure 1: Employment across job regimes, 2012 and 2025



Note: Share of total employment (per cent), 2012 (2011–12) and 2025; workers aged 15–64. Workers (million), 2025, estimated as population × work participation rate × regime share by age and sex. High-routine occupations (regimes 2 + 4).

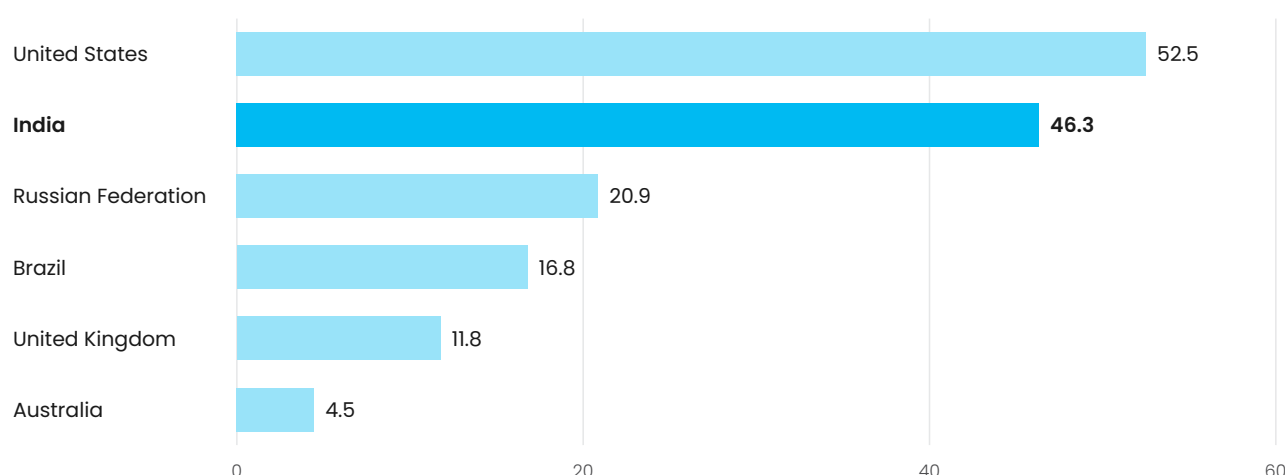
Source: Authors’ calculations.

- Even with less than 8 per cent of the employed in AI-complementary occupations, India has one of the largest workforces that can directly raise productivity through effective use of AI tools and expert domain knowledge (Figure 2). With access to cheap AI tools, Indian IT companies can automate the lower-value, routine layers of their work – testing, maintenance, basic coding – and redeploy talent towards higher-value work

such as system design, AI integration, and product strategy, moving up the value chain rather than being displaced by it.

- About 5.6 per cent is in exposed work where the balance between augmentation and substitution is still open, including ICT professionals and technicians, business and administration professionals, and personal service and care workers (Figure 1).

Figure 2: Workers in AI-complementary occupations: India and selected countries, 2025 (million)



Note: Employed persons (million) in AI-exposed, high-complementarity, low-routine occupations (regime 1), 2025. For India, workers aged 15–64 are estimated as population × work participation rate × regime share by age and sex. For other countries, ILO estimates of employment for all ages by occupation are classified using the same occupation-level scores and thresholds as India. China is not shown as comparable occupational data are not available.

Source: Authors' calculations based on ILO population estimates⁵ and PLFS 2025 for India.

- The remaining 11.4 per cent is in exposed work facing substitution pressure both from AI and conventional automation – clerical and sales work of various kinds – where reskilling and task redesign can move occupations towards complementarity before that pressure settles⁶.
- The three-quarters of employment with low AI exposure divides into two very different groups. About 21.0 per cent (127.5 million) is in low AI exposure but highly routine work: food preparation assistants, cleaners and helpers, machine operators, garment and food processing trades, and construction and manufacturing labourers.
- The largest occupation regime, at 54.4 per cent of employment in India in 2025 (around 326 million), is low exposure and low routine. It includes agriculture and farm and primary sector occupations, as well as skilled trades such as metal and machinery workers, building trades, electrical and electronics trades, drivers, and plant operators (Mahambare, 2023b). India as well as several other countries currently reports shortages in these occupations, and they are insulated from both AI and task-based automation.
- Between 2012 and 2025, the low-exposure, low-routine regime shrank by 6.2 percentage points and the exposed, balance-open regime by 0.8 points. About two-thirds of this shift went into high-routine work (regimes 2 and 4 together rose 4.8 points), and about a third into the complementary regime (up 2.3 points). Part of this shift reflects a structural transformation out of low-productivity farm and informal work into clerical, sales, and routine manufacturing jobs, which raises measured exposure and routine intensity even where pay and conditions improve for the workers involved.

⁵ In the absence of age-specific data, estimates for other countries cover employed persons of all ages. The majority of employed in India fall within ages 15–64.

⁶ This group includes own-account shopkeepers and traders, who account for 3.8 per cent of total employment in 2025, up from 2.0 per cent in 2012 (from 1.2 to 3.0 per cent in rural areas and from 4.5 to 5.6 per cent in urban areas). They are classified as AI-exposed, low-complementarity and high-routine because they belong to the two-digit occupation Sales Workers (NCO-2015 52), whose scores reflect the standardised, transactional tasks of cashiers, shop assistants and counter staff, such as billing, cash handling, stocking and recording sales. The occupation's routine task intensity (0.035) lies only marginally above the threshold. Because the indices are available only at the two-digit level and classification rests on fixed cut-offs, this assignment likely overstates the routine content and substitution pressure facing shopkeepers, whose work also involves purchasing, pricing, credit, and customer management.

Because routine intensity governs exposure to conventional automation independently of AI, this widens the relevant policy question: a substantial part of the workforce has moved towards work susceptible to capital substitution that predates generative AI. Overall, the policy task is not to reduce exposure but to improve its quality – to expand the complementary regime rather than to slow the technology.

Routine content makes this work technically automatable, but technical feasibility is not the same as economic viability, and at India's relative factor prices the capital cost of replacing these workers often exceeds the wage cost of employing them (Vashisht and Rani, 2019). Substitution pressure here is therefore weaker than the task content alone

would suggest. Also, in sectors such as textiles, where turnover is high, automation is better understood as a response to labour scarcity than as a threat to employment.

3.2 Regime Shares by Age Group

- AI exposure is concentrated in early career and declines steadily thereafter. About 29 per cent of workers aged 25–34 are in AI-exposed occupations, 10.0 percentage points above the 55–64 cohort at about 19 per cent, with a monotonic decline across the intervening bands.
- Complementary work accounts for approximately one-third of exposed employment among workers aged 25–54; the remaining two-thirds of exposed employment in these ages is not complementary.

Figure 3: Job regimes by age group, 2025



Note: Share of each age group's employment by regime (per cent); workers aged 15–64 (million), estimated as population × work participation rate × regime share by age and sex. All ages uses headline survey-weighted shares, which may differ slightly from shares implied by the millions.

Source: Authors' calculations.

- In the 15–24 age cohort the AI complementary share of exposed employment is lower, at 22.4 per cent, and it has the highest share

of high-routine employment in the workforce, at 39.4 per cent against 24.2 per cent for the 55–64 cohort. This age group is most

vulnerable to technology replacing human workers.

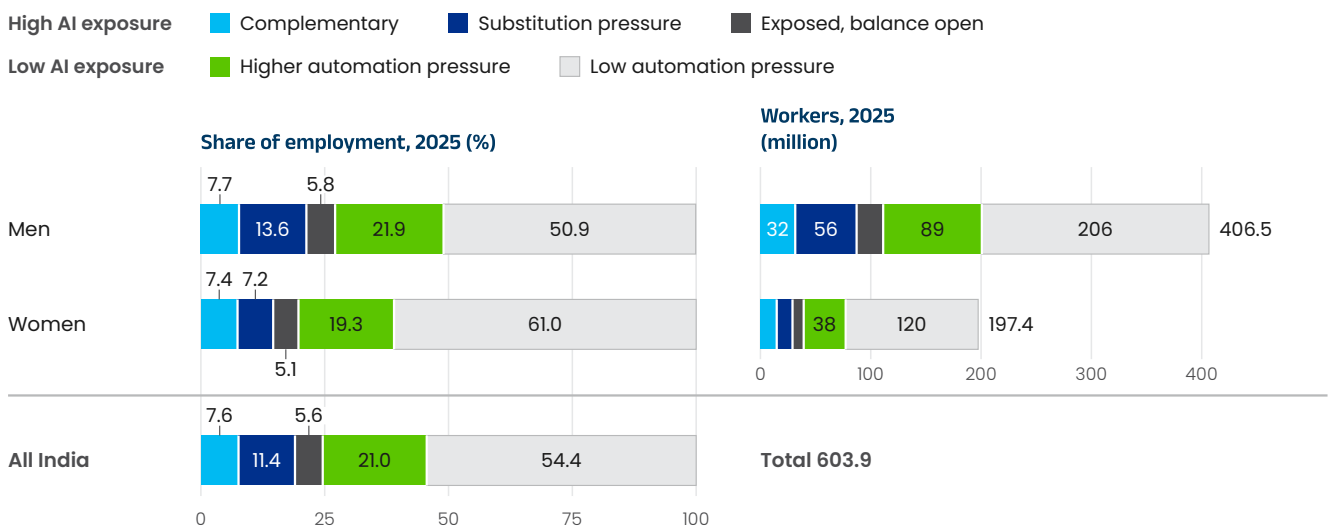
- The lower exposure of older cohorts reflects occupational composition rather than skill protection: their insulated share of 66 per cent reflects concentration in agriculture and manual trades, which the routine-intensity measure classifies as non-routine. This does not rule out displacement through farm mechanisation, which the index does not capture.

3.3 Regime Shares by Gender

- Women's employment is less exposed overall: 61.0 per cent of female employment remains in the low-exposure, low-routine regime, largely farm work, against about 51 per cent for men.

The exposure women do have is of better quality. The complementary share of women's AI-exposed employment is 37.6 per cent against 28.4 per cent for men in 2025, and their substitution-to-complementary ratio is 0.97 against 1.77 – the only group at parity. This reflects the concentration of women's exposed employment in health and teaching occupations, which are non-routine and interaction-intensive.

Figure 4: Job regimes in men's and women's employment, 2025



Note: Share of employment by regime (per cent); workers aged 15–64 (million), estimated as population × work participation rate × regime share by age and sex, so they may differ slightly from the survey-weighted shares.
Source: Authors' calculations.

- At the national level, there is gender parity in AI-complementarity employment rates, but in absolute numbers men dominate, given their higher overall employment rates (in 2025: male 7.7 per cent, 31.6 million; female 7.4 per cent, 14.8 million). Compared to 2012, however, the complementary share of exposed employment rose from 21.6 to 28.4 per cent for men but eased from 40.1 to 37.6 per cent for women, as much of women's growth in exposed employment was in sales and clerical work.

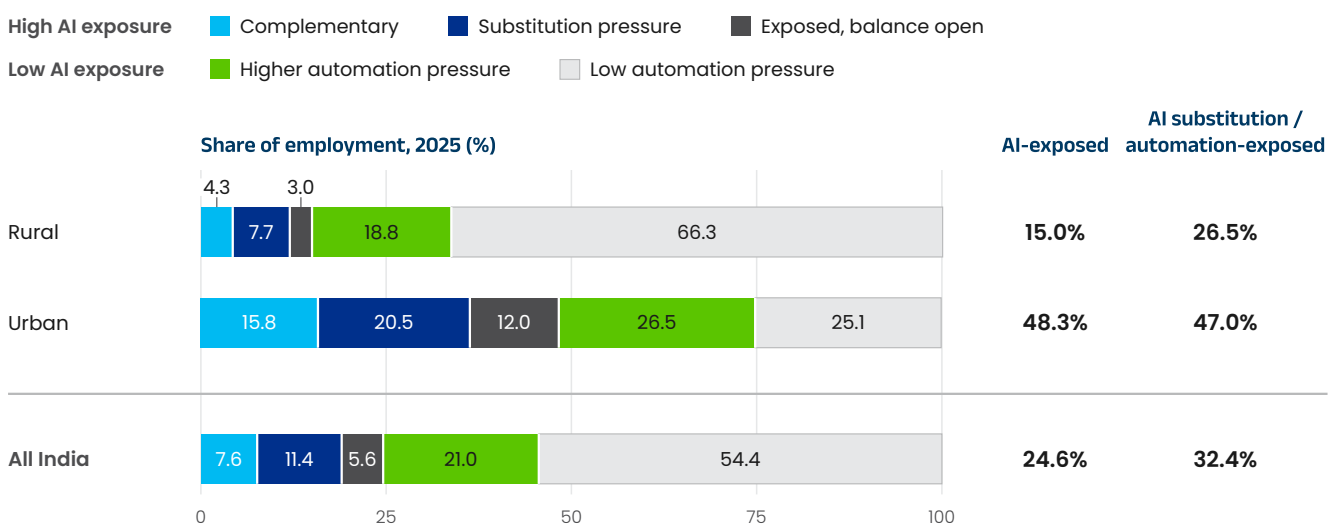
3.4 Regime Shares by Location: Rural and Urban

- Total AI-exposed employment accounted for 15.0 per cent of rural employment in 2025 against 48.3 per cent in urban India. Exposure quality improved in both. The complementary share of exposed employment rose from 23.5 to 28.7 per cent in rural areas and from 26.3 to 32.7 per cent in urban areas, and the substitution-to-complementary ratio fell from 1.96 to 1.79 in rural India and from 1.65 to 1.30 in urban India.

Rural employment in the low-exposure, low-routine regime fell 7.1 percentage points between 2012 and 2025. Most of this moved into high-routine work, which rose 6.2 points (4.0 in low-exposure routine work and 2.2 in substitution-pressure work), while the complementary regime gained 1.5 points. Rural diversification away from agriculture is therefore mainly into routine-intensive work rather than into the complementary regime.

- In urban India, the complementary regime rose 3.5 percentage points to 15.8 per cent, the largest gain of any regime, while the balance-open regime fell 2.2 points and the substitution-pressure regime was broadly unchanged at 20.5 per cent. With roughly half of urban employment exposed, urban India retains both the largest complementary base to build from and the largest population for whom AI literacy and task redesign would translate directly into productivity.

Figure 5: Job regimes in rural and urban employment, 2025



Note: AI-exposed = regimes 1–3; High-routine occupations (regimes 2 + 4).
Source: Authors' calculations.

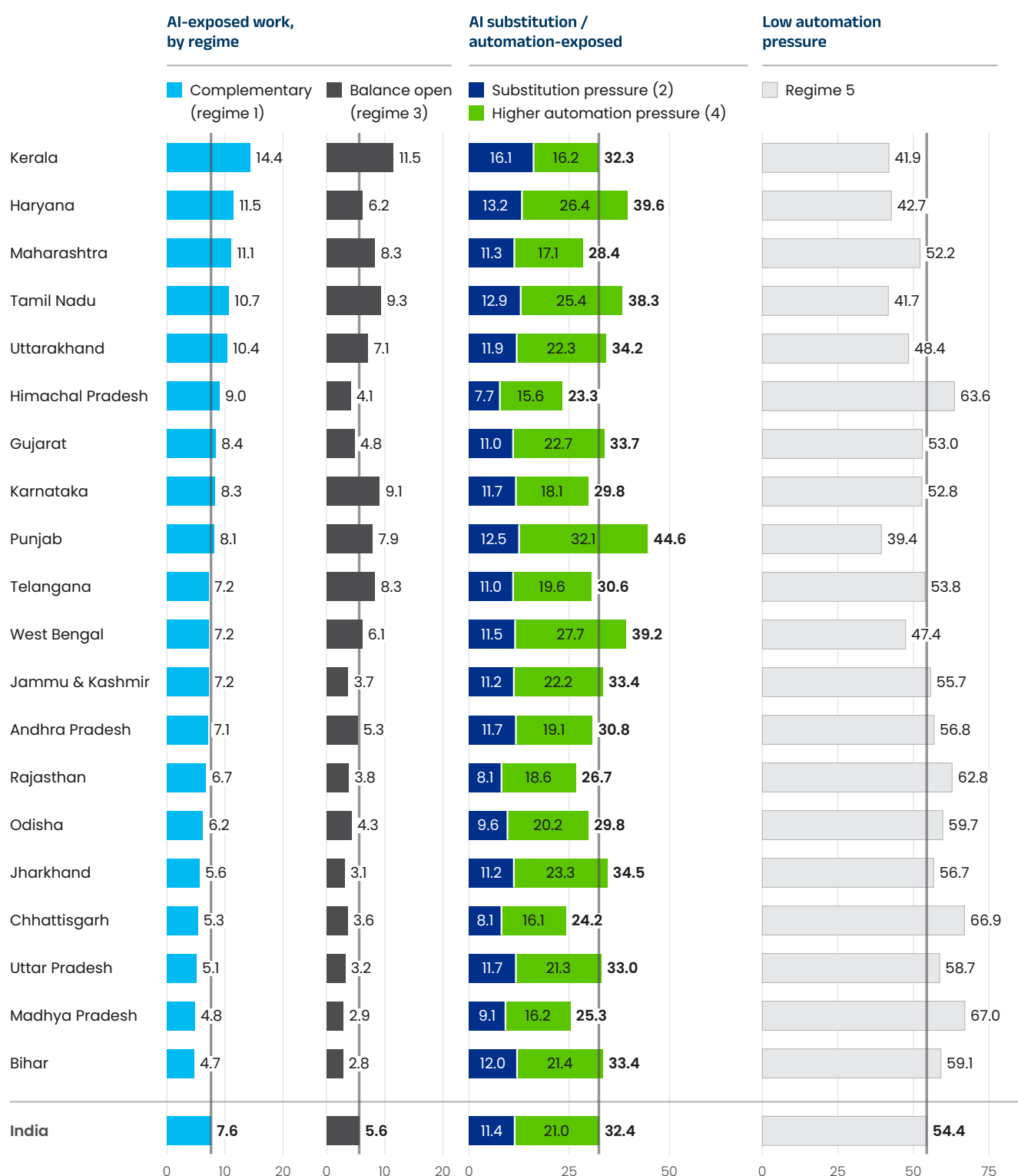
3.5 State-Level Patterns

- The share of employment in AI-exposed occupations ranges from 42.0 per cent in Kerala to 16.8 per cent in Madhya Pradesh. Kerala is an outlier. It is the only state in which AI-exposed employment (42.0 per cent) is as large as the low AI and low automation exposure share (41.9 per cent). In all other states, the insulated regime is larger, and in Madhya Pradesh it is four times larger.
- The level of exposure says little about its quality at the state level (Figure 6). Himachal Pradesh has modest AI-exposure at 20.8 per cent, yet the highest complementary share of exposed employment among major

states, at 43.3 per cent, with more exposed workers standing to be augmented than displaced. Rajasthan shows the same disjunction from the other direction, ranking eighteenth on exposure but fourth on complementary share at 36.0 per cent.

- The southern states' lead is in quantity of AI-exposure, not quality. The five southern states average 30.9 per cent employment share in AI-exposed occupations, while Uttar Pradesh, Bihar, Rajasthan, Jharkhand, Chhattisgarh and Madhya Pradesh cluster in a narrow 16.8 to 20.0 per cent band at the bottom. But the southern average complementary share, at 30.4 per cent, is marginally below the national figure.

Figure 6: Job regimes by state, 2025



Note: Per cent of state employment, 20 major states, sorted by complementary share (regime 1). Grey lines mark India.

Source: Authors' calculations.

- Karnataka and Telangana are the clearest instances: sixth and eighth on AI-exposure but fifteenth and eighteenth on AI-complementary share of exposed employment, at

28.5 and 27.2 per cent. What distinguishes them is the size of the third regime - AI-exposed, low-complementarity, non-routine work, largely ICT professionals and techni-

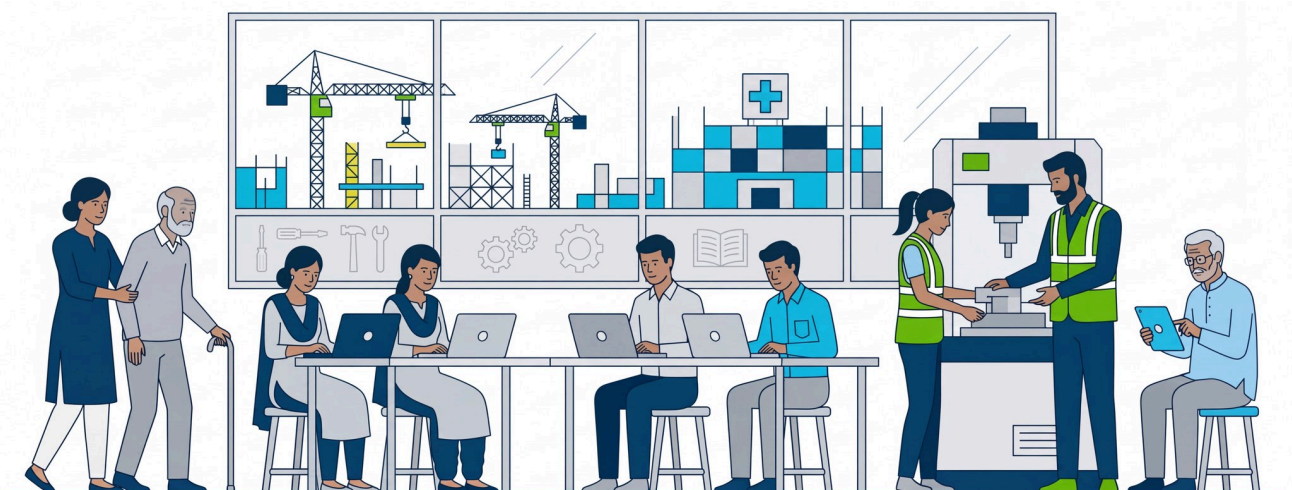
cians and business and administration professionals – which accounts for 31.3 per cent of exposed employment in both states against 22.8 per cent nationally, the highest among major states. Because the augmentation-substitution balance remains unresolved in this regime, the two states offer the greatest leverage for task redesign and AI literacy per worker reached, while Kerala, Maharashtra, Haryana and Tamil Nadu have the highest complementary shares of employment to build from.

- The relatively low-income populous states face a double disadvantage. For example, Uttar Pradesh, Bihar, Jharkhand and Madhya Pradesh average 19.0 per cent employment in AI-exposed occupations against 24.6 per cent nationally, and a complementary share of exposed employment at 26.6 per cent against 30.9 per cent. They have less AI-exposed employment, and what exists is more substitutable: in Bihar, 61.5 per cent of AI-exposed employment is in the substitution-pressure regime against only 24.1 per cent in the complementary one. These states are behind the technological frontier rather than insulated from it, so the policy task is to create complementary work rather

than to defend existing exposed work – which points directly to the shortage sectors in health, education and care where their service deficits are also largest.

- Routine content maps differently from AI exposure, correlating with it only partly across the 20 major states, and so identifies a partly separate set of at-risk states. Punjab carries the heaviest routine burden at 44.6 per cent, followed by Haryana at 39.6, West Bengal at 39.2 and Tamil Nadu at 38.3; Himachal Pradesh at 23.3, Chhattisgarh at 24.2 and Madhya Pradesh at 25.3 carry the lightest.
- Punjab is the most automation-exposed state on the combined measure, with the highest routine content and the smallest insulated regime among major states at 39.4 per cent. Its routine share reflects construction and manufacturing labourers, sales workers and food-processing and garment trades rather than agriculture, which falls in the low-routine regime. Routine manufacturing, processing and construction work are likely drivers across the high-routine states, and involve capital substitution unrelated to generative AI.

4. Policy Implications



Below we list key policy suggestions to make India's workforce AI- and automation-ready. The first three – AI literacy, targeted reskilling and the shortage-sector channel – address how to make the workforce ready for the future and the remainder address the conditions that allow those three to work.

4.1 Make AI literacy near-universal

What this means in practice

1. Set a minimum requirement for AI practice in Classes 6 to 12 through NCERT and State Boards and support schools in addressing equipment gaps through convergence funds.
2. Create a single, clearly branded AI entitlement for adults in the form of a subsidised credit for tools and training, rather than a catalogue of courses, delivered through Skill India Digital Hub with assisted enrolment at Common Service Centres and ITIs. Scale the subsidy by income so that those who can least afford AI tools receive greater support. Fund it partly through corporate social responsibility (CSR) contributions.
3. Link stipends to completion rather than enrolment, and keep training short, modular and flexible so that self-employed workers do not lose income by participating.
4. Redesign curricula across NSQF, ITIs, poly-

technics, engineering and commerce to build domain knowledge, communication skills and the ability to exercise judgement in situations of uncertainty, rather than simply teaching familiarity with AI tools.

AI literacy – knowing how to use AI tools well – is the cheapest lever available for India, since it requires no new physical infrastructure and can be embedded in existing curricula and skilling programmes. India's experience with cheap data and smartphones is instructive: a technology with substantial learning potential has been absorbed overwhelmingly into consumption and entertainment rather than skill acquisition. AI use may follow the same path by default unless literacy is taught as a work practice.

In the complementary, non-routine regime, high-quality AI literacy is what converts exposure into higher productivity, including in the public sector. In the regime where the balance between augmentation and substitution remains open, literacy, combined with deliberate task redesign, tilts occupations towards complementarity before substitution sets in by default. Literacy programmes should be evaluated on demonstrated use in actual work tasks, not on modules completed or certification acquired.

The digital divide means the least-exposed

workers are also the least able to capture the upside of AI augmentation. Subsidised tool access should therefore be directed to the poor and middle class, who otherwise face the access paradox of being insulated from AI and excluded from its gains. Mahambare and Venugopalan (2026) argue that AI literacy should be treated as basic infrastructure – as the digital public infrastructure stack was for payments – rather than as a stand-alone training programme.

4.2 Target reskilling, new tasks and occupation creation

What this means in practice

1. *Add judgement-intensive service trades and task modules to apprenticeship and short-term skilling programmes, combining classroom or basic training with supervised workplace exposure.*
2. *Include an industry-supervised capstone in AICTE-approved engineering programmes in which students solve real workplace problems using both domain knowledge and AI tools.*
3. *Prioritise workers in routine clerical, back-office and low-discretion technical occupations for training in judgement, problem solving, client engagement and supervisory tasks.*
4. *Build training capacity in exposed occupations before employment losses materialise, rather than relying primarily on post-displacement retraining.*
5. *Encourage upskilling of the AI-complementary workforce towards higher value-added information-technology and Global Capability Centre (GCC) roles, and encourage AI start-ups that help other firms overcome AI-adoption bottlenecks and deploy AI to raise labour productivity.*

One in five urban workers remains in AI-exposed, low-complementarity, routine work. Reskilling budgets should be directed at this regime rather than spread evenly across the

workforce. Reskilling should also anticipate the occupations AI creates, not only those it erodes – such as the ‘prompt specialist’ role identified early in generative AI diffusion (Mahambare, 2023c), which can be performed remotely from smaller Indian cities, though its wage premium is likely to narrow as supply rises.

Two features of this adjustment make young entrants the priority group, consistent with the age profile in Section 3.2. First, a large share of India’s million-plus engineering graduates each year has been absorbed by IT services for exactly the routine coding and testing that AI now automates, so as entry-level demand softens, these graduates need engineering skills that complement AI rather than duplicate it (Mahambare and Venugopalan, 2026). Second, AI systems are trained on past data and cannot anticipate major deviations from established trends, so the judgement required to foresee such shifts – which accrues with experience and practice – rises in value, and it becomes correspondingly harder for young workers to establish themselves as experts when everyone has access to super-knowledgeable machines (Mahambare, 2023a). Entry-level programmes should therefore focus on supervised exposure to real judgement-intensive tasks rather than tool-operation modules alone.

China’s experience shows both who bears the adjustment and how fast it arrives: a one-standard-deviation rise in industrial robot exposure cut labour-force participation by 1 per cent, employment by 7 per cent and hourly earnings by 8 per cent, concentrated among less-educated, prime-age and older men, with voluntary retraining rising only after exposure rather than pre-empting it (Giuntella, Lu and Wang, 2025).

Because technology adoption responds to labour cost – a 10 per cent minimum wage rise raised a Chinese firm’s probability of adopting a robot by 0.11 percentage points, concentrated among more productive, coastal and private firms (Fan, Hu and Tang, 2021) – reskilling capa-

city should be built ahead of future minimum-wage increases, not after them.

4.3 Turn the shortage sectors into an absorption channel

What this means in practice

1. *Create a National Skills Qualifications Framework tier for nursing and care work, foundational teaching and the skilled trades that is formally equivalent to a degree, with an upward rung above it so the track has a visible summit.*
2. *Sequence investment before publicity: upgrade ITIs, nursing schools and teacher-training colleges first, then run a sustained recognition campaign pitched at parents as much as at workers.*
3. *Ease credit access, business registration and digital-platform matching for self-employed tradespeople, so this work is an entrepreneurial entry point rather than a job of last resort.*
4. *Support the AI-infrastructure sectors – energy, water, healthcare including bio-medical trials, submarine cable capacity, and high-speed data-transfer and repair capacity – so that the cost of AI-enabling utilities remains affordable for businesses.*
5. *Target the low-income populous states – Uttar Pradesh, Bihar, Jharkhand, Madhya Pradesh – with the shortage-sector channel first, alongside factory employment and value-added agro-processing for the low-exposure farm workforce.*

Shortage occupations in health and education are non-routine, high-complementarity occupations whose employment share has barely grown since 2012; elderly care falls in the exposed, low-complementarity regime and the skilled trades in the insulated regime (Table 2) partly because the jobs carry weak credentials, low social standing, and the lack of a career ladder. Kuriakose and Kylasam Iyer (2018), drawing on the ILO's 2018 report on care work (ILO, 2018), note that sustained investment in

education, health and social enterprises could generate some 269 million jobs globally by 2030, with disproportionate benefit to women, who perform over three-quarters of current unpaid care work.

Mahambare and Venugopalan (2026) make the same point for India: elderly care, nursing and healthcare involve long hours, unpleasant conditions and shift work; teaching has lost status; and the skilled trades – driving, plumbing, electrical work and personal services – pay decently but carry little social prestige. Yet this group, spanning a wide mix of education and skill levels, is the largest and the most overlooked, and it holds the biggest untapped source of new middle-class livelihoods if the work can be made to pay and to command respect. Germany's dual system achieves parity with academic education through nationally standardised, portable credentials across recognised occupations, governance shared between states, chambers, unions and training firms, and a quality floor that requires firms to be certified before they may train.

China's 2011 elderly-caregiver qualification ladder had to drop its educational requirement and ease its experience requirements by 2019 because they deterred entrants (Ministry of Human Resources and Social Security & Ministry of Civil Affairs, 2019). In this context, NITI Aayog's Care Economy Vision (NITI Aayog, 2026) sets out the right design – a National Caregiver Council, common training standards, recognition of prior learning, social security and international mobility pathways – but India spends under 1 per cent of GDP on the care economy, and ASHA and Anganwadi workers remain on honorariums rather than wages. The mobility pathway will only grow more valuable: ageing high-income countries will keep demanding care workers whose work depends on physical presence even as AI narrows the routine IT-driven emigration route.

No study in India or a comparable economy isolates the effect of a social-status intervention on labour supply while holding pay and training content constant – a measurement

gap worth closing before committing large sums to prestige-building campaigns. Two instruments are nonetheless available now. The first is credential parity: Germany's Meister qualification is benchmarked to Level 6 of its national framework, formally equivalent to a bachelor's degree (UNESCO-UNEVOC, 2026) – naming a qualification to signal parity is the cheapest status intervention available.

The second is a perception campaign backed by substance: Singapore reversed the stigma on technical education by overhauling curricula and rebuilding institutes around applied learning (Law, 2014), not by publicity alone, so that most of its weakest-performing quartile now graduates into decently paid work.

Because many of these occupations sit within heavily regulated industries, how quickly these channels open depends on India's regulatory regime becoming simpler and more predictable – regulatory reform is, in this sense, employment policy.

4.4 Raise learning and completion together

What this means in practice

1. *Support the transition from Class 10 to 11, where the enrolment gap is largest, by expanding higher secondary sections in existing schools and providing targeted support such as transport and hostels.*
2. *Link skilling funding to learning outcomes, with funding tied to measurable gains in literacy, numeracy and problem solving rather than the number of certificates issued.*
3. *Strengthen the general education component of vocational training by setting a minimum share of literacy, numeracy, problem solving, articulation and negotiation in every NSQF-aligned course.*
4. *Make logic, problem solving and analytical thinking part of everyday teaching from the early grades, rather than treating them as separate modules.*
5. *Give students greater flexibility in what they*

study and how they are assessed by allowing subject combinations across streams and giving greater weight to oral, viva and practical assessment in Classes 11 and 12 and undergraduate programmes.

As tasks get automated and work profiles are redesigned, the returns will increasingly accrue to resourcefulness, integrative thinking, and articulation and analytical thinking, raising the value of the humanities and of the ability to integrate knowledge across disciplines (Mahambare, 2023a). These skills let workers move across tasks and occupations rather than master a single, fixed skill set (Autor, 2015; Deming, 2017). Deming and Noray (2020) show that technical skills depreciate fastest in the most technology-intensive occupations, so early earnings advantages erode as the skill content of the work changes unless workers keep learning.

Autor et al. (2026) find, in a randomised trial of patent lawyers, that three months of AI assistance improved later unassisted performance only among senior lawyers, suggesting that foundational expertise may be a prerequisite for durable gains from AI-assisted work. Bentaouet Kattan, Macdonald and Patrinos (2018) find that post-secondary attainment and literacy achievement are consistently associated with holding a non-automation-prone occupation, and that openness and extraversion are also positively associated with it in several countries – evidence that the protective factor is measured skill, not certification alone. Their finding on vocational education is a direct caution for India's skilling architecture: secondary vocational programmes generally confer no advantage in avoiding automation-prone occupations and in several countries raise the likelihood of ending up in one, because they concentrate on narrow technical content, de-emphasise cognitive and non-cognitive skills, and recruit students already behind on exactly those skills.

China's higher-education expansion is a cautionary precedent on the enrolment margin:

annual university enrolment rose from roughly one million to over 6.3 million within a decade of the 1999 reform, partly to relieve short-run employment pressure, and was followed by rising graduate unemployment (Li, Whalley and Xing, 2014) – a burden that fell on the young because the extra graduate supply raised the college premium for older cohorts and lowered it for younger ones, young and senior skilled workers proving to be complements rather than substitutes (Li et al., 2017).

Embedding logic, problem-solving and analytical thinking from the early grades is the supply-side response to the employability gap, and it moves future workers towards the complementary regime rather than the contracting one; it also counters the rote-credential model that produces degrees that do not pay. Two design changes follow. School and college systems should be flexible enough to permit combinations of subjects across functional streams – computer science with psychology, business studies and mathematics, for instance – which is not currently feasible, since narrow specialisation in a single domain without the ability to integrate knowledge across disciplines will no longer be sufficient. Assessment needs rethinking for the same reason: once conversational AI is widely available at low cost, conventional take-home assignments and written examinations no longer distinguish between students unless very creatively designed, and plagiarism detection becomes progressively more time-consuming and futile, which argues for a shift towards oral and viva-based assessment despite the difficulty of scaling it (Mahambare, 2023a).

4.5 Build on women's position in complementary work

What this means in practice

1. *Make it easier for women to take up employment by expanding childcare facilities near or within schools (starting with pilots), providing safe transport and, for single women, affordable and safe accommodation in urban areas, including through*

working women's hostels and similar institutions.

2. *Create more pathways into complementary jobs in health, care, teaching and other roles where human judgement and interaction remain valuable. Support women returning to work after career breaks.*

As Section 3.3 shows, women hold the near-parity substitution-to-complementary ratio (0.97 against 1.77 for men), reflecting their concentration in non-routine, interaction-intensive health and teaching work. This differs from the cross-country picture. Pizzinelli et al. (2023) and Cazzaniga et al. (2025) find that women face greater occupational exposure to AI than men, and ILO (2026) estimates place around 29 per cent of female-dominated occupations in the exposed category against about 16 per cent of male-dominated ones. These results describe the urban clerical and services tail of women's employment, which is small in India. Because most female employment remains in the low-exposure, low-routine regime, India's aggregate position is more favourable than the cross-country evidence would predict, and the risk it identifies applies to a specific urban segment rather than to women's employment as a whole.

Two features of the analysis point to where the opportunity lies. First, women's growth in exposed employment is mainly in sales and clerical work, with a smaller rise in the exposed, low-routine regime, where task redesign has the most leverage and where men's share of employment has fallen. Second, because young women's movement out of agriculture would continue through education, its destination remains open. The shortage sectors identified in Section 4.3 – health and teaching – are precisely the complementary occupations in which women's exposed employment is already concentrated, so expanding them serves as the absorption channel and the gender strategy at the same time.

Women's participation in the labour market, not exposure, is the binding constraint. About 18

per cent of women aged 20 to 29 are in paid work, compared with roughly 79 per cent of men in the same age band, based on the Time Use Survey 2024 data, despite near-parity in educational attainment (Mahambare et al., 2026a). Raising that figure, and directing the resulting entry towards complementary occupations, would do more for women's position than any defensive measure. Childcare provision at appropriate locations (near or in schools), safe transport, and safe and affordable accommodation for single women in urban areas are labour-market policies in this context as shown in the case of Tamil Nadu (Mahambare et al., 2026b), rather than welfare adjuncts, and scaling the existing working-women hostel and Sakhi Niwas provisions is a faster route than building a new scheme. Reskilling programmes should be designed and located so that women can reach them.

Two considerations cut in opposite directions. In women's favour, the soft skills they tend to hold an advantage in – communication, empathy, coordination, client interaction – become tomorrow's hard skills as engineering tasks automate, reinforcing their complementarity advantage (Mahambare, 2023a). Against this, machine-generated output raises the premium on in-person interaction and travel to establish expertise, and a return to presence-based advancement would reverse remote work's gains for women unless childcare, safe accommodation, and the domestic division of labour are addressed alongside it.

4.6 Reorganise social protection

What this means in practice

1. *Social protection benefits should be linked to the individual worker and remain with them as they move between platforms, employers, states or periods of self-employment.*
2. *Workers should be enrolled automatically, with the option to opt out, rather than having to apply for benefits themselves.*
3. *Workers leaving routine occupations should*

receive temporary transition support to help them move into new jobs without placing the full burden on their families.

Automation is changing not only which jobs exist but the form of the employment relationship: work is increasingly a portfolio of discrete tasks performed at task-specific rates, often through platforms, which weakens employer obligations on minimum wages, social benefits and collective bargaining. India's starting point has improved but remains partial. ILO data record that the share of India's population covered by at least one social protection benefit rose from 24.4 per cent in 2021 to 48.8 per cent in 2024 (ILO, 2024), and to 64.3 per cent in 2025 based on the first phase of a national data-pooling exercise (ILO, 2025b).

The labour-share evidence points the same way. If the aggregate labour share falls mainly because activity reallocates towards low labour-share firms rather than because firms automate (Bárány, Patel and Siegel, 2026b; Autor et al., 2020), then workers' share of income is protected by their ability to move to where value is created. That makes protection that travels with the worker, rather than with the employer, the relevant instrument. The Chinese evidence shows what happens when that instrument is absent. Giuntella, Lu and Wang (2025) find that households exposed to robot adoption held consumption and savings steady only by increasing borrowing by around 10 per cent, and that exposed workers were significantly more likely to retire early. Without portable protection, adjustment costs do not disappear; they shift to household balance sheets and premature withdrawal from the labour force.

4.7 Restructure the labour subsidy

What this means in practice

1. *Under wage subsidy schemes, firms should receive greater support for training workers in AI-complementary skills and helping them use AI tools effectively.*
2. *Hiring and training incentives should focus*

on occupations with stronger long-term potential, particularly health, care, education and other roles where human skills remain important.

3. *Apprenticeships should offer more training in AI-complementary skills and the care economy, with stipends updated to make these opportunities more attractive.*

India's labour subsidies currently pay to add a formal body to a payroll and keep it there – the employment-linked incentive of up to ₹3,000 a month per additional hire, the four-year manufacturing bonus, the apprenticeship stipend share (Ministry of Labour and Employment, 2025). That architecture pays for headcount at a moment when the binding question is capability. Four reorientations follow from the regime analysis.

First, pay for developing capability: redirect support from payroll top-ups towards verified AI-complementary training and the co-funded deployment of AI tools to workers, which is the firm-side counterpart to subsidised AI literacy and what converts a worker's exposure into complementarity rather than displacement. Second, target by regime: direct hiring and training incentives towards the high-complementarity occupations and taper support for purely routine, automatable roles.

Third, re-weight from manufacturing headcount towards the resilient service occupations – care, health and education – where subsidies that professionalise, certify and raise wages address the staffing shortage and the prestige problem together, which a headcount bonus does not; this is reinforced by manufacturing's own trajectory, since more automated expansion keeps adding to the economy but with falling labour intensity (Mahambare and Venugopalan, 2026), so headcount-linked support buys progressively less employment per rupee. Fourth, the National Apprenticeship Promotion Scheme already shares apprentice stipend and training costs rather than payroll cost, so re-pointing its trades towards AI-complementary skills and the care economy, and

lifting its dated stipend caps, is the cheaper reform.

4.8 Treat housing and commuting as labour-market infrastructure



What this means in practice

1. *Shift the housing subsidy towards urban areas and, within urban housing, away from the credit-linked interest subsidy for buyers towards affordable rental, building out the affordable rental housing complex component.*
2. *Nudge states to adopt the model tenancy legislation to bring vacant private units into the formal rental market.*
3. *Prioritise bus fleet and frequency in secondary cities over capital-intensive rail where the objective is labour-market access.*

Exposure is not the only thing that determines whether a worker can move towards complementary work; the ability to physically reach where that work is matters as much. Jobs concentrate in cities, and labour cannot move there without affordable urban rental housing. India's housing subsidy is rural-skewed (Mahambare, 2024), and its urban component is largely a credit-linked interest subsidy for buyers rather than support for the rental housing a rural-to-urban migrant actually needs. Housing support should enable mobility instead of anchoring workers where the jobs are not. Urban commuting infrastructure belongs in the same category. Treating housing and transport as labour-market infrastruc-

ture rather than welfare makes the reskilling recommendations above operational, since a worker who cannot afford to live near the work cannot take it.

4.9 Support the reinstatement channel in the data economy

What this means in practice

1. *Publish a model contract and minimum standards for labelling, annotation and comparable digital platform work, and bring these workers within the portable social protection architecture.*
2. *Create progression pathways from routine digital gig work into AI evaluation, domain-specific annotation, expert validation and supervisory tasks, with portable credentials that workers can carry across platforms and employers.*
3. *Build applied expertise in medicine, law, engineering and Indic languages while treating expert-generated training data as a skilled services export opportunity rather than low-skill work.*
4. *Promote portability of verified skills, work experience and, where feasible, platform reputation so that workers are not locked into a single intermediary for access to future work.*
5. *Track the share of data- and platform-economy earnings coming from expert and complementary tasks rather than routine annotation as the indicator of whether the channel is moving up the value chain.*

Technology displaces tasks but also reinstates demand for new ones (Acemoglu and Restrepo, 2019), and India's emerging data economy provides a present-day example. Roughly 50,000 freelance and 20,000 full-time data annotators were working in India in 2024; NASSCOM (2024) projects that India could service over 7 billion US dollars of the global annotation market by 2030; and NITI Aayog's 2018 national AI strategy (NITI Aayog, 2018) identified annotation as work capable of

absorbing automation-displaced labour. More than 80 per cent of providers' workforce comes from non-metro cities, making this a genuine small-town employment opportunity that few sectors offer. Most of this work currently sits in the low-complementarity cells as human-in-the-loop labour, with real risks of de-skilling, gig precarity and eventual substitution as models become more capable.

This distinction is important because the gig economy itself should not be treated as either inherently vulnerable to or protected from AI. Platform-mediated physical work, such as mobility, delivery, care, repair and personal services, may remain relatively insulated because it requires physical presence and human interaction. Routine digital gig work, by contrast, including basic annotation, transcription, content processing and other codifiable tasks, can be directly exposed to the same technologies that initially create demand for it. AI can therefore expand platform-based forms of employment while simultaneously reducing demand for particular platform tasks.

The policy objective should consequently be to make gig work a transition ladder rather than a low-productivity holding zone. Workers entering through routine digital tasks should have pathways towards higher-value activities requiring verification, contextual judgement, domain knowledge, client interaction and supervision. This would move workers from low-complementarity tasks towards work in which AI augments rather than substitutes for human capability.

A second and higher-value layer of this channel is already visible. Frontier AI laboratories contract Indian doctors, lawyers, engineers and language specialists to generate and evaluate expert training data, including through AI-driven clinical trials in healthcare, and specialists competent in both English and Indic languages command a premium for training Indic-language models (Mahambare and Venugopalan, 2026). Unlike routine annotation, this work draws on professional judgement and is correspondingly harder to automate,

although the window in which particular tasks earn a premium may itself be finite.

4.10 Build continuous measurement

What this means in practice

1. *Develop a regular labour-market monitoring framework that combines PLFS occupational data with National Career Service vacancies, e-Shram data, online job postings and industry hiring information to track emerging changes in occupational demand, skill requirements and technological exposure.*

India needs a labour-market measurement system that can identify changes in occupations and skill demand more quickly than periodic survey comparisons alone. The PLFS should remain the statistical backbone because it provides representative information on employment and occupational structure, but it can be complemented by more frequent signals from National Career Service vacancies, e-Shram, staffing firms, online job postings, sector associations and industry bodies such as NASSCOM. Together, these sources can indicate which occupations are expanding or contracting, which skills employers are increasingly demanding, and where the task content of existing jobs is changing as AI and automation diffuse.

The five occupational regimes developed in this study illustrate why such continuous measurement matters. They provide an analytical framework for distinguishing between employment that is relatively exposed to AI, potentially complementary with AI, susceptible to routine automation, or comparatively insulated. However, these categories should not themselves be treated as a fixed official classification. The underlying technologies, tasks and occupational requirements will change over time, and measures of AI exposure and complementarity will need to be periodically reassessed as technological capabilities evolve.

These signals can then be periodically mapped to updated measures of technological exposure and complementarity. Such a system would provide an early-warning mechanism for policymakers. A rise in vacancies for AI-complementary occupations could signal where education and training capacity should expand, while declining demand or changing skill requirements in routine occupations could identify where reskilling is needed before displacement becomes visible in employment statistics. The objective is not to predict which jobs will disappear, but to detect changes early enough for education, skilling and labour-market policy to respond.

5. Conclusions

The share of Indian employment exposed to AI has risen modestly since 2012, and the quality of that exposure has improved: the share with a realistic chance of AI complementarity has risen, although fewer than 8 per cent of the employed were in these occupations in 2025. The ratio of substitution-pressure to complementary work has fallen. But substitution-pressure work still outweighs complementary work by half. The policy task that follows is not to slow the technology's spread but to raise the complementary share – through near-universal AI literacy, raising expertise in domain

knowledge, and reskilling targeted specifically at those who are currently in AI-exposed, low-complementarity regimes and support for workers in AI complementarity occupations, including in the public sector, where AI adoption could be slower.

A second, and in India's case larger, transition is running in parallel and predates generative AI: the share of employment in routine work exposed to automation pressure rose by 4.8 percentage points between 2012 and 2025. Because this shift can be anticipated well

before disruption hits, building reskilling capacity now is cheaper than retraining displaced workers later.

The most promising opportunity is to turn India's chronic shortages in health, education and care work, and trade skills into the primary absorption channel for a growing workforce, while ensuring these occupations pay and carry social status – through credential parity, portable social protection, and financing that follows workers rather than employers.

None of this holds without addressing who bears the adjustment cost. Young labour-

market entrants carry the largest share of exposure in low AI-complementarity/high routine work and the least protection from it; women hold a genuine but under-exploited advantage in complementary work that participation constraints, not technology, are holding back; and the populous low income states face the compounded burden of both less exposure and a worse mix of what exposure they have. Making AI literacy near-universal, redirecting subsidies from headcount to capability, and measuring these shifts continuously together determine whether India can convert this transition into broad-based productivity gains.

Appendix

A1. Data and Analytical Sample

The empirical analysis combines harmonised employment microdata covering two rounds of India's labour-force surveys: 2011-12 and 2025. The surveys are appended into a common individual-level database and represented analytically by the reference years 2012 and 2025. The analysis is restricted to individuals identified as employed, and survey weights are used in estimating employment distributions and workforce-level averages.

A central issue in constructing the historical series is the change in occupational classification across survey rounds. The 2011-12 round reports occupations according to NCO-2004, whereas the 2025 PLFS uses NCO-2015. NCO-2004 was developed in correspondence with ISCO-88, while NCO-2015 reflects the subsequent restructuring of occupational classifications associated with ISCO-08. Consequently, occupational codes cannot always be treated as directly comparable across the two systems.

A2. Comparability of the 2011-12 Employment-Unemployment Survey and the 2025 PLFS

The two endpoints used in the analysis come from different generations of India's official labour-force survey system. The 2011-12 data are drawn from the 68th Round Employment and Unemployment Survey (EUS) of the National Sample Survey, conducted from July 2011 to June 2012 using Schedule 10. The survey covered the year through four three-month sub-rounds, with sample first-stage units distributed across the survey period. The 2025 data are drawn from the Periodic Labour Force Survey (PLFS) for calendar year 2025, using the first-visit unit-level data for January to December 2025.

The survey designs are not identical. The 2011-12 EUS was a cross-sectional household survey based on a stratified multi-stage sampling design. Its first-stage units were Census villages in rural areas and Urban Frame Survey blocks in urban areas, with households forming the ultimate-stage units. The survey was designed to generate comprehensive employment and unemployment estimates at the national and State/UT levels. The 2025 PLFS operates under the modified methodology introduced

from January 2025 and uses a rotational panel design. Selected households are scheduled for four visits over four consecutive months: one first visit and three revisits. The design supports monthly and quarterly Current Weekly Status estimates, while annual level estimates continue to be generated using usual status.

For the present analysis, however, the purpose is not to compare high-frequency labour-market indicators generated under the two survey designs. The analysis uses the surveys to estimate the distribution of employed persons across occupations and subsequently across the five technological regimes. In both survey systems, information is available on workers' employment status and occupation. The 2011-12 EUS records usual principal and subsidiary economic activities as well as occupation for persons engaged in economic activity, while the PLFS annual framework similarly provides employment indicators in usual status (principal plus subsidiary status) and distributions of workers by occupation.

Accordingly, the analytical sample uses a common employment concept based on usual status (principal plus subsidiary status). The occupational distributions are estimated separately within each survey using the corresponding survey weights. The 2025 unit-level documentation specifically requires applying the survey multiplier to generate estimates. The comparison therefore does not pool observations as if they were generated under an identical survey design; rather, each survey is used to recover a survey-weighted occupational distribution for its respective period.

A further comparability issue arises from occupational classification. The 2011-12 Schedule 10 records occupation using NCO-2004 at the three-digit level, whereas the 2025 PLFS uses NCO-2015. This difference is addressed through the occupational harmonisation procedure described in the following section, after which technological characteristics are attached to the harmonised occupational groups.

The comparison should nevertheless be interpreted with appropriate caution. Changes between 2011-12 and 2025 may reflect both genuine changes in India's occupational structure and differences

associated with survey design, sampling and occupational classification. For this reason, the analysis does not interpret small changes in narrowly defined occupations as precise longitudinal movements. Instead, it focuses on large, economically meaningful changes in the survey-weighted shares of employment across five broad technological regimes. The use of broad occupational regimes, a common usual-status employment concept, occupational harmonisation and survey-specific weights provides a consistent basis for examining structural differences in the technological composition of employment across the two endpoints, while recognising that the underlying surveys are not methodologically identical.

A3. Harmonisation of Occupational Codes

A3.1. Concordance

To obtain a consistent occupational classification over time, we concoded occupations reported under NCO-2004 to the NCO-2015 structure using the official NCO-2015/NCO-2004 concordance published by the Directorate General of Employment. The official concordance is considerably more detailed than the occupational information available in the labour-force microdata. While the concordance identifies individual occupations at detailed code levels, the survey data used in the analysis identify occupations only up to the three-digit level. Exact occupation-to-occupation matching is therefore not feasible for every worker.

Consequently, we implemented the concordance in two stages. First, we reduced both NCO-2004 and NCO-2015 occupational codes to a common three-digit level. Where all detailed NCO-2004 occupations in an older three-digit group were reassigned to the same NCO-2015 three-digit group, the corresponding old group was recoded directly to that destination group.

A small number of cases involve one-to-many correspondence. That is, detailed occupations contained within a single NCO-2004 three-digit group were redistributed across more than one NCO-2015 three-digit group. Because the labour-force surveys do not provide the additional occupational digits needed to distinguish these detailed occupations, we cannot uniquely concord these cases at the individual-worker level. For these groups, we adopted a modal (majority) concordance rule: we assigned the old three-digit group to the NCO-2015

three-digit group that received the most detailed occupational correspondences in the official concordance.

This procedure prioritises consistency of the occupational time series while retaining substantially more information than harmonisation directly at the two-digit level. Nevertheless, it introduces a limited degree of classification error for occupational groups whose detailed constituent occupations were split across multiple NCO-2015 groups. The historical results should therefore not be interpreted as representing perfectly reconstructed NCO-2015 occupations for every individual worker.

This limitation matters less for the present analysis for two reasons. First, the AI exposure, AI complementarity and routine-task measures used subsequently are attached at the broader two-digit occupational level. Reclassification among three-digit occupations located within the same two-digit group therefore leaves the relevant technological indicators unchanged. Second, the principal outcome is a five-category Future-of-Jobs classification constructed from these broad technological dimensions. Thus, even where the concordance places a three-digit occupation in a different two-digit group, this affects the substantive classification only when the destination group also belongs to a different technological regime.

Accordingly, the historical series, particularly the five-regime occupational distribution, best describes broad changes in the technological composition of Indian employment rather than precise movements of narrowly defined occupations. The harmonisation procedure may introduce measurement error at the margins of occupational categories, but it is unlikely to mechanically generate the broad structural trends that the analysis focuses on.

A3.2. Self-employed workers in managerial occupations

The two classifications differ in how small business owners are recorded, and the concordance does not resolve this difference. In 2011-12, workers coded in NCO-2004 Division 1 (Legislators, Senior Officials and Managers) were predominantly heads of household enterprises rather than salaried managers. Most were coded under Directors and Chief Executives (NCO-2004 121), of whom over 90 per cent were own-account workers or unpaid family

helpers and fewer than 1 per cent were regular salaried employees. Under the concordance, these workers map into NCO-2015 Administrative and Commercial Managers and hence into the AI-exposed, complementary regime. In PLFS 2025, by contrast, most workers in managerial occupations are regular salaried employees, and small proprietors are recorded in the occupation of their enterprise's activity. In particular, NCO-2015 intro-

duces a separate Shopkeepers family (5221) within Sales Workers that has no counterpart in the NCO-2004 concordance, so no 2011-12 worker can be concorded into it. Applying the concordance alone would therefore classify the same type of worker – a small proprietor running a shop, workshop or transport business – as a manager in 2011-12 but as a sales, craft or transport worker in 2025.

Table A1: Assignment of Self-Employed Workers Coded as Managers in 2011-12, by Industry

Industry (NIC-2008)	Assigned occupation (NCO-2015)
Wholesale and retail trade, including sale and repair of motor vehicles (45-47)*	Sales Workers (52)
Land, water and air transport (49-51)	Drivers and Mobile Plant Operators (83)
Food, beverages, tobacco, textiles, apparel, leather, wood, furniture (10-16, 31)	Food Processing, Wood Working, Garment and Other Craft and Related Trades Workers (75)
Metals, metal products, machinery, vehicles, repair of machinery (24-25, 28-30, 33)	Metal, Machinery and Related Trades Workers (72)
Electronics, electrical equipment, electricity, repair of household goods (26-27, 35, 95)	Electrical and Electronic Trades Workers (74)
Paper, printing, non-metallic minerals, other manufacturing (17-18, 23, 32)	Handicraft and Printing Workers (73)
Mining; petroleum, chemicals, pharmaceuticals, rubber and plastics (05-09, 19-22)	Stationary Plant and Machine Operators (81)
Construction (41-43)	Building and Related Trades Workers (71)
Accommodation and food service (55-56)	Personal Service Workers (51)
Agriculture (01)	Skilled Agricultural Workers (61)
Forestry and fishing (02-03)	Forestry and Fishery Workers (62)
Other industries	Occupation corresponding to the principal activity of the industry**

Note: *Includes self-employed workers in motor-vehicle repair, many of whom also sell spare parts and accessories.

**For example, information and communication (58-63) to ICT Technicians (35); finance and real estate (64-66, 68) to Business and Administration Associates (33); education (85) to Teaching Professionals (23); health (86) to Health Professionals (22); and personal services (96) to Personal Service Workers (51). The industry-based assignment was not applied to employers. Unlike own-account workers, who mainly perform the enterprise's activity themselves, employers also hire and direct others, and the data do not show whether their work is mainly managerial. Employers form a small share of managers in 2011-12 (about 4 per cent) and of proprietors in PLFS 2025 (about 4 per cent), so we retained them as coded: employer-managers in 2011-12 as managers, and employer-proprietors in PLFS 2025 in the occupation corresponding to their activity. This does not affect the findings.

Source: Authors' classification based on NIC-2008 and NCO-2015.

The two surveys record industry and occupation separately. Industry, classified under NIC-2008 in both rounds, describes the enterprise's economic activity, while occupation, classified under NCO, describes the tasks the worker performs. For an own-account worker or unpaid family helper in a household enterprise, the two are closely linked: a

person running a retail shop mainly sells, a person running a tailoring unit mainly sews, and a person operating a goods vehicle mainly drives. Because industry is recorded on the same NIC-2008 basis in both surveys, it provides a consistent anchor for identifying the tasks of self-employed workers

whose occupation was recorded as managerial in 2011-12.

Following the principle that occupation is determined by the tasks performed rather than by employment status, we assigned own-account workers and unpaid family helpers coded in NCO-2004 Division 1 (codes 111-130) in 2011-12 the NCO-2015 occupation corresponding to the principal activity of their industry, at the NIC-2008 two-digit level. The principal assignments are as follows.

Employers were retained in managerial occupations. Unlike own-account workers, they hire and direct others' work. We retained regular salaried and casual workers in managerial occupations as coded, and did not adjust the 2025 data. The procedure reassigns about 5.5 per cent of 2011-12 employment. After reassignment, managerial occupations (NCO-2015 11-14) account for 1.3 per cent of employment in 2011-12 and 2.7 per cent in 2025, indicating that the two rounds are coded comparably.

The assignment is made at the level of the industry's principal activity and cannot capture variation within industries. For example, a self-employed worker in furniture manufacturing may work mainly as a carpenter or mainly as a finishing or assembly worker. Division 45 also includes the maintenance and repair of motor vehicles; self-employed workers in this activity, many of whom combine repair with the sale of spare parts and accessories, are assigned to Sales Workers together with other traders. Because the occupational indices are attached at the two-digit level, such variation matters only where alternative occupations fall in different regimes. The largest group of reassigned workers, own-account traders, is assigned to Sales Workers in line with both the NCO-2015 treatment of shopkeepers and the official concordance's mapping of NCO-2004 retail and wholesale dealers to Sales Workers.

A4. Linking Occupations to Technological Characteristics

Following occupational harmonisation, each employed worker is assigned the technological characteristics corresponding to the worker's harmonised two-digit NCO-2015 occupational group. Three occupation-level measures are used: AI exposure, AI complementarity and routine task

intensity. These measures are held constant across survey rounds.

Consequently, changes in aggregate AI exposure, complementarity, routine intensity and Future-of-Jobs regime shares over time arise from changes in the distribution of workers across occupations rather than from changes in the occupation-specific technological scores themselves. The historical exercise therefore measures whether India's employment structure has moved towards occupations that, from the perspective of contemporary technological capabilities, are relatively more AI-exposed, complementary or routine-intensive. It does not imply that AI itself caused historical employment changes.

A5. Occupational Measures of Technological Exposure and Task Content

The analysis adopts a multidimensional approach to technological susceptibility by combining three occupation-level measures: routine task intensity, AI exposure and AI complementarity. Rather than constructing these indices independently, the analysis uses the occupation-level measures reported in the accompanying data to the World Bank's *Future Jobs: Robots, Artificial Intelligence, and Digital Platforms in East Asia and Pacific* (Arias et al., 2025). The World Bank framework brings together measures derived from Autor and Dorn (2013), Felten, Raj and Seamans (2021), and Pizzinelli et al. (2023) and reports them at the two-digit occupational level.

For occupation o , its technological position is represented by

$$T_o = (AI_o, COMP_o, RTI_o)$$

where AI_o denotes AI occupational exposure, $COMP_o$ denotes AI complementarity and RTI_o denotes routine task intensity.

The three measures capture related but conceptually distinct dimensions of technological change. Routine task intensity captures the extent to which occupational tasks are repetitive and codifiable. AI exposure captures the extent to which occupational tasks overlap with capabilities associated with artificial intelligence. Complementarity captures the extent to which an occupation's characteristics make AI more likely to augment human work than substitute for it.

Using these measures jointly matters because

technological exposure alone does not determine the likely nature of technological transformation. Occupations with similar AI exposure may differ considerably in their complementarity with AI, while occupations with relatively little direct AI exposure may nevertheless remain susceptible to conventional automation because of high routine task intensity.

Routine Task Intensity

The analysis uses the routine task intensity measure from the occupation-level data accompanying Arias et al. (2025). The World Bank report applies the task-based framework associated with Autor and Dorn (2013), using occupational task information to provide a relative ordering of occupations by routine task intensity.

Higher RTI values indicate occupations containing relatively greater concentrations of repetitive and codifiable tasks, whereas lower values indicate greater reliance on non-routine activities. The measure therefore captures a dimension of technological susceptibility that extends beyond artificial intelligence. Highly routine occupations may be susceptible to automation, software-based automation, robotics or other forms of capital substitution even where direct AI exposure is limited.

AI Exposure

The AI exposure measure is also taken directly from the occupation-level data accompanying Arias et al. (2025) and originates from the occupational AI exposure framework of Felten, Raj and Seamans (2021). It measures the extent to which the tasks associated with an occupation overlap with capabilities affected by developments in artificial intelligence.

Importantly, AI exposure is not interpreted as an estimate of job displacement. High exposure indicates that AI is technologically relevant to a relatively large component of the occupation's task structure. Whether this exposure results in substitution, augmentation or a reorganisation of tasks depends on the characteristics of the occupation and the manner in which the technology is adopted.

AI Complementarity

The AI complementarity measure is taken from the same World Bank occupation-level data and draws on Pizzinelli et al. (2023). Complementarity provides a means of distinguishing occupations in which

exposure to AI is more likely to involve augmentation from occupations in which exposure may carry greater substitution potential.

Higher complementarity characterises occupations in which human involvement remains important because of factors such as judgement, responsibility, interpersonal interaction or other characteristics that limit the extent to which tasks can be transferred entirely to AI. AI exposure and complementarity are therefore considered jointly rather than treating all highly exposed occupations as technologically equivalent.

The occupation-level values of all three measures are taken as reported in the World Bank data rather than re-estimated using the underlying O*NET task information or reconstructed from the original studies.

AI Exposure and Complementarity Regimes

Following the World Bank framework, AI exposure and AI complementarity are considered jointly. The AI exposure measure has a natural threshold at zero. Occupations with an AI exposure score greater than zero are classified as AI-exposed, while occupations with a score less than or equal to zero are classified as having low AI exposure.

Formally, occupation o is classified as AI-exposed when

$$AI_o > 0,$$

and as low AI exposure when

$$AI_o \leq 0.$$

Among AI-exposed occupations, complementarity is used to distinguish the likely nature of human-AI interaction. Let M_{COMP} denote the employment-weighted mean of the occupation-level AI complementarity measure, using 2025 employment weights. An AI-exposed occupation is classified as having high complementarity when

$$COMP_o > M_{COMP},$$

and low complementarity when

$$COMP_o \leq M_{COMP}.$$

This produces three broad AI-related occupational positions: high AI exposure with high complementarity, high AI exposure with low complementarity, and low AI exposure.

Among occupations with positive AI exposure, the

complementarity measure distinguishes between two substantively different forms of technological exposure. High-exposure occupations with high complementarity are interpreted as occupations in which AI has relatively greater potential to augment human work, whereas high-exposure occupations with low complementarity are interpreted as facing relatively greater potential for task substitution.

Occupations with AI exposure less than or equal to zero are classified as low-exposure occupations and are not further divided according to complementarity. In these occupations, AI has comparatively limited direct relevance to the occupational task structure, making the distinction between high and low complementarity less informative for the present classification.

The resulting AI classification therefore consists initially of three groups:

$$AIRegime_o = \begin{cases} 1 & \text{High exposure, high complementarity} \\ 2 & \text{High exposure, low complementarity} \\ 3 & \text{Low exposure.} \end{cases}$$

These categories describe technological positioning rather than realised employment effects and should not be interpreted as predictions of job displacement or job creation.

The complementarity threshold is the 2025 employment-weighted mean across all occupations. Weighting by employment ensures that the threshold reflects the occupations in which Indian workers are actually employed and anchors the classification to India's occupational structure rather than to the cross-country sample of Pizzinelli et al. (2023). The 2025 weights describe the current employment structure and are coded directly in NCO-2015, and the threshold is held fixed across both rounds so changes in regime shares reflect worker movement rather than shifts in the cut-off.

With a lower cut-off, such as the unweighted mean or median, Legal, Social, Cultural and Related Associates, Personal Service Workers and Personal Care Workers would be classified as complementary. The complementary regime would then be larger in both years, with a smaller increase between 2012 and 2025, but the direction of change is unaffected. These assignments should therefore be interpreted with caution.

Incorporating Routine Task Intensity

The AI exposure-complementarity classification does not fully capture the broader technological susceptibility of occupations. This is particularly relevant in the Indian labour market, where a substantial share of workers remains employed in occupations involving routine physical or cognitive tasks.

An occupation may have relatively low exposure to contemporary AI while nevertheless consisting largely of repetitive and codifiable activities. Such occupations may remain susceptible to conventional automation, robotics or other forms of capital substitution. Consequently, low AI exposure should not automatically be interpreted as technological security.

Routine task intensity is therefore incorporated as a third dimension. As with AI exposure, zero is used as the threshold for distinguishing relatively routine from relatively non-routine occupations. Occupation o is classified as high routine when

$$RTI_o > 0,$$

and as low routine when

$$RTI_o \leq 0.$$

A positive RTI score indicates that the occupation is relatively more intensive in routine tasks, while a score of zero or below indicates relatively greater non-routine task intensity.

Table A2: Classification of Occupations into Future-of-Jobs Regimes

Regime	AI exposure	AI complementarity	RTI	Interpretation
1	High	High	Low	AI-exposed, complementary, low-routine
2	High	Low	High	AI-exposed, low-complementarity, high-routine
3	High	Low	Low	AI-exposed, low-complementarity, low-routine
4	Low	Either	High	Low AI exposure, high-routine
5	Low	Either	Low	Low AI exposure, low-routine

Note: AI exposure (Felten, Raj and Seamans, 2021) and routine task intensity (Autor and Dorn, 2013) are classified high when greater than zero. AI complementarity (Pizzinelli et al., 2023) is classified high when above the 2025 employment-weighted mean (0.581), and applies to AI-exposed occupations only.

Source: Authors' classification based on Arias et al. (2025), Felten, Raj and Seamans (2021), Pizzinelli et al. (2023) and Autor and Dorn (2013).

The three technological dimensions are then combined to construct five Future-of-Jobs occupational regimes:

The resulting classification extends the AI exposure-complementarity framework by explicitly incorporating routine intensity. This is useful for the Indian context because technological transformation is unlikely to occur exclusively through AI. Conventional automation remains relevant for occupations characterised by routine tasks but limited direct exposure to AI.

The five categories should therefore be interpreted as broad technological regimes rather than forecasts of whether particular occupations will disappear, expand or remain unchanged.

It should be noted that two categories lie close to their thresholds. Legal, Social, Cultural and Related Associates have a complementarity score (0.5805) marginally below the threshold, and Sales Workers have a routine task intensity (0.035) only marginally above zero. These assignments should be interpreted with corresponding caution.

A6. Alternative Measures of AI Exposure and

Choice of Index

Several measures of occupational AI exposure are now available, and they differ in what they measure, the technology they cover and the occupational classification they use. The Felten, Raj and Seamans (2021) index used in this study measures potential AI exposure. It links the abilities an occupation requires, such as image recognition, language comprehension and pattern detection, to progress in broad AI capabilities rather than to any particular AI model. High exposure thus indicates that AI is relevant to the abilities an occupation uses. Whether this leads to productivity gains or displacement depends on whether AI complements or substitutes for those abilities, which is why this approach combines exposure with complementarity. More recent measures focus on generative AI. The ILO (2025a) index scores each ISCO-08 task on the potential for generative AI to perform it without human involvement, combining language-model predictions, a worker survey and expert review, and aggregates task scores to occupations. It therefore measures current exposure in tasks as performed today, not potential exposure arising from AI capabilities. Eloundou et al. (2024) rate task exposure to large language models on the US O*NET-SOC classification, so applying their measure to India would require further crosswalks to ISCO-08 and NCO-2015, adding classification error.

Table A3: AI Exposure Classification of Occupations: ILO (2025a) and Felten, Raj and Seamans (2021)

ISCO-08 / NCO-2015	Occupation Title	Based on Felten, Raj and Seamans (2021)	Based on ILO (2025a)
11	Chief Executives, Senior Officials and Legislators	AI Exposed	AI Exposed
12	Administrative and Commercial Managers	AI Exposed	AI Exposed
13	Production and Specialized Services Managers	AI Exposed	AI Exposed
14	Hospitality, Retail and Other Services Managers	AI Exposed	AI Exposed
21	Science and Engineering Professionals	AI Exposed	AI Exposed
22	Health Professionals	AI Exposed	AI Not Exposed
23	Teaching Professionals	AI Exposed	AI Exposed
24	Business and Administration Professionals	AI Exposed	AI Exposed
25	ICT Professionals	AI Exposed	AI Exposed
26	Legal, Social and Cultural Professionals	AI Exposed	AI Exposed
31	Science and Engineering Associate	AI Not Exposed	AI Exposed
32	Health Associate	AI Exposed	AI Not Exposed
33	Business and Administration Associate	AI Exposed	AI Exposed
34	Legal, Social, Cultural and Related Associate	AI Exposed	AI Exposed
35	ICT Technicians	AI Exposed	AI Exposed
41	General and Keyboard Clerks	AI Exposed	AI Exposed
42	Customer Services Clerks	AI Exposed	AI Exposed
43	Numerical and Material Recording Clerks	AI Exposed	AI Exposed
44	Other Clerical Support Workers	AI Exposed	AI Exposed
51	Personal Service Workers	AI Exposed	AI Not Exposed
52	Sales Workers	AI Exposed	AI Exposed
53	Personal Care Workers	AI Exposed	AI Not Exposed
54	Protective Services Workers	AI Not Exposed	AI Not Exposed
61	Skilled Agricultural Workers	AI Not Exposed	AI Not Exposed
62	Skilled Forestry, Fishery and Hunting Workers	AI Not Exposed	AI Not Exposed
63	Subsistence Farmers	AI Not Exposed	AI Not Exposed
71	Building and Related Trades Workers	AI Not Exposed	AI Not Exposed
72	Metal, Machinery and Related Trades Workers	AI Not Exposed	AI Not Exposed
73	Handicraft and Printing Workers	AI Not Exposed	AI Not Exposed
74	Electrical and Electronics Trades Workers	AI Not Exposed	AI Not Exposed
75	Food Processing, Garment, Related Trades Workers	AI Not Exposed	AI Not Exposed
81	Stationary Plant and Machine Operators	AI Not Exposed	AI Not Exposed
82	Assemblers	AI Not Exposed	AI Not Exposed
83	Drivers and Mobile Plant Operators	AI Not Exposed	AI Not Exposed
91	Cleaners and Helpers	AI Not Exposed	AI Not Exposed
92	Agricultural, Forestry and Fishery Labourers	AI Not Exposed	AI Not Exposed
93	Construction & Manufacturing Labourers	AI Not Exposed	AI Not Exposed
94	Food Preparation Assistants	AI Not Exposed	AI Not Exposed
95	Street and Related Sales and Service Workers*		AI Not Exposed
96	Refuse Workers and Other Elementary Workers	AI Not Exposed	AI Not Exposed

Note: ILO (2025a) scores are simple averages of four-digit ISCO-08 occupation scores, standardised across the 40 two-digit occupations; Felten, Raj and Seamans (2021) scores are from Arias et al. (2025). An occupation is AI exposed when its standardised score is above zero. *Occupation code 95 (Street and Related Sales and Service Workers) has no routine task intensity score and is therefore excluded from the five-regime classification and its denominator.
Source: Authors' calculations based on ILO (2025a) and Arias et al. (2025).

To test whether the choice matters, the ILO (2025a) scores were aggregated to the two-digit level and

compared with the classification used here (Table A3). The two indices classify almost all occupations

alike, and the few differences reflect what each measures. Health professionals, health associate professionals, personal service workers and personal care workers are exposed under the Felten index but not the ILO index, while science and engineering associate professionals lie at the threshold. Health professionals, for example, are exposed under the Felten index because interpreting medical images and diagnostic information draws on abilities that overlap with AI capabilities. They score lower in the ILO assessment because humans currently perform most clinical tasks, such as examinations, procedures, and patient care, even though AI could perform parts of them. The two indices therefore differ in purpose but largely agree in direction: the ILO index reflects how the work is done today, while the Felten index captures what AI could do, which is why the complementarity dimension is needed to judge whether that potential will augment or replace workers.

The Felten index is preferred for several reasons. Because it is based on AI capabilities rather than current models, it identifies where AI can become relevant as adoption spreads, whereas a measure of current task automation may understate exposure where capabilities are relevant but not yet applied. It underlies the complementarity measure of Pizzinelli et al. (2023), so exposure and complementarity are measured consistently. Neither ILO (2025a) nor Eloundou et al. (2024) offers a matching complementarity measure, without which augmentation cannot be separated from substitution as the regime framework requires. Arias et al. (2025) report the index with complementarity and routine task intensity at the ISCO two-digit level, so all three can be combined directly with the harmonised NCO-2015 occupations in the Indian surveys.

Because it is fixed and capability-based, it can also be applied to the 2012 and 2025 occupational structures on the same basis and supports the international comparison in Figure 2. The index predates large language models, which may appear to be a limitation. However, its purpose here is to capture potential rather than current exposure to any particular technology, which is what comparing occupational structures between 2012 and 2025, and assessing future exposure, requires. The occupations most affected by large language models, such as clerical and ICT work, are already classified as exposed.

A7. Employment Shares across Future-of-Jobs Regimes

Following the construction of the five Future-of-Jobs regimes, each employed worker is assigned to the regime corresponding to the worker's harmonised two-digit occupation. The empirical analysis then estimates the survey-weighted share of employment in each regime rather than treating the occupation-level AI exposure, complementarity and routine-task indices as worker-level outcomes in themselves.

Let $R_o = k$ indicate that occupation o belongs to regime k , where $k = 1, \dots, 5$, and let w_{it} denote the survey weight of employed individual i in year t . The employment share of regime k in year t is calculated as

$$S_{kt} = \frac{\sum_i w_{it} 1(R_{oi} = k)}{\sum_i w_{it}},$$

where $1(\cdot)$ is an indicator function equal to one when the occupation of worker i belongs to regime k , and zero otherwise.

The five regime shares exhaust the employed workforce in each survey round and therefore sum to 100 per cent. The analysis compares these shares between 2011-12 and 2025 to examine changes in the technological composition of Indian employment.

The five regimes distinguish employment in: (i) AI-exposed, complementary and low-routine occupations; (ii) AI-exposed, low-complementarity and high-routine occupations; (iii) AI-exposed, low-complementarity and low-routine occupations; (iv) low-AI-exposure and high-routine occupations; and (v) low-AI-exposure and low-routine occupations.

This formulation is particularly useful for the historical analysis because the occupation-specific technological measures are held fixed. Changes in regime shares therefore arise from changes in the distribution of employment across occupations rather than from changes in the underlying AI exposure, complementarity or RTI scores assigned to a given occupation. The analysis consequently captures structural movement of the workforce across occupational regimes defined using contemporary technological characteristics.

For example, an increase in the employment share of AI-exposed and complementary occupations

does not imply that AI itself created those jobs. It indicates that a larger proportion of the workforce is employed in occupations that, according to contemporary task and technological measures, combine relatively high AI exposure with relatively high complementarity.

The regime-based approach is also preferable to considering AI exposure in isolation because occupations with similar exposure can differ substantially in their complementarity with AI and in routine task intensity. It therefore allows the historical analysis to distinguish between movement towards occupations with greater potential for AI augmentation, occupations facing relatively greater substitution pressure, and occupations whose technological susceptibility is associated more closely with conventional automation.

A8. Rural-Urban and Gender Composition of Technological Regimes

The employment-share framework is first extended across rural and urban labour markets and by gender. For sector of residence r , gender g , regime k and year t , the corresponding employment share is calculated as

$$S_{k,r,g,t} = \frac{\sum_{i \in (r,g)} w_{it} 1(R_{oi} = k)}{\sum_{i \in (r,g)} w_{it}}.$$

This produces a complete five-regime employment distribution separately for rural men, rural women, urban men and urban women, as well as the corresponding rural, urban and overall distributions.

The purpose of this decomposition is to identify whether changes in India's aggregate technological employment structure are shared across labour-market segments or are concentrated within particular groups. Differences across gender or rural-urban location are interpreted as differences in occupational composition rather than differences in the technological characteristics of the same occupation. A higher share of women in a particular regime, for example, reflects their greater concentration in occupations assigned to that regime.

A9. Age Profile of Future-of-Jobs Regimes

The analysis further examines the distribution of workers across the five technological regimes by age. Workers are classified into five age groups: 15-24, 25-34, 35-44, 45-54 and 55-64. Regime shares

are calculated separately for each age group, survey year, gender and rural-urban location.

For age group a , the weighted employment share of regime k is

$$S_{k,a,t} = \frac{\sum_{i \in a} w_{it} 1(R_{oi} = k)}{\sum_{i \in a} w_{it}}.$$

The age decomposition permits an examination of whether occupational technological positioning differs across generations and whether younger workers are entering a different occupational structure from older workers. Particular attention is given to whether younger workers are increasingly concentrated in AI-exposed and complementary occupations or remain concentrated in occupations characterised by low AI exposure or high routine intensity.

Because these are repeated cross-sectional surveys, differences across age groups are interpreted descriptively and should not be treated as pure cohort effects. Observed differences may reflect a combination of cohort characteristics, age-related occupational sorting and changes in the overall structure of employment.

A10. Geography of Technological Transformation

The five-regime framework is also applied at the state level. For state s , regime k and year t , the survey-weighted employment share is calculated as

$$S_{k,s,t} = \frac{\sum_{i \in s} w_{it} 1(R_{oi} = k)}{\sum_{i \in s} w_{it}}.$$

The same calculation is undertaken separately for rural and urban workers within each state. This produces state-year distributions showing the proportion of employment located in each of the five technological regimes.

The geographical analysis therefore focuses on differences in the occupational composition of employment across regimes, rather than on assigning different technological scores to the same occupation in different states. Occupation-specific AI exposure, complementarity and RTI remain fixed; states differ because their workers are distributed differently across occupations.

This allows the analysis to identify whether some state labour markets are relatively more concen-

trated in AI-exposed and complementary occupations, while others remain dominated by low-AI-exposure or routine-intensive employment. Changes in these shares over time indicate the direction in which the occupational structure of individual states has evolved.

The state-level results should be interpreted as measures of relative technological positioning rather than direct measures of technology adoption. A state with a relatively high share of AI-exposed employment is not necessarily using more AI. Rather, it has a larger share of workers in occupations whose task characteristics are currently assessed as more exposed to AI.

A11. Interpretation and Scope

The empirical exercise is structural rather than causal. The AI exposure, AI complementarity and routine task intensity measures are fixed occupation-level characteristics, while the labour-force surveys identify how workers are distributed across occupations and, consequently, across the five Future-of-Jobs regimes.

The central empirical outcome is therefore the employment share associated with each technological regime. Changes in these shares indicate changes in India's occupational structure relative to contemporary technological characteristics. They do not identify employment gains or losses caused by artificial intelligence, automation or other technologies.

This distinction matters because the historical series begins in 2011-12, well before the recent diffusion of generative AI. For example, an increase between 2012 and 2025 in the share of workers classified as AI-exposed and complementary means that employment has shifted towards occupations that are more exposed and complementary to AI today. It does not imply that AI

caused that occupational shift over the historical period.

A further consideration concerns occupational harmonisation across survey rounds. Because the earlier surveys provide occupational information only at the three-digit level, some detailed changes between NCO-2004 and NCO-2015 cannot be recovered exactly and require the modal concordance procedure described above. This may introduce limited classification error at the occupational margin; however, its implications are reduced because the technological indicators are attached at the broader two-digit level and the principal results aggregate employment into five broad occupational regimes.

The technological indices themselves also represent broad occupational averages. The same AI exposure, complementarity and RTI values are assigned to workers belonging to the same two-digit occupation, although the precise tasks performed by workers within an occupation may vary across firms, locations and individuals. The resulting categories should therefore be interpreted as measures of broad technological positioning rather than exact assessments of the technological susceptibility of every individual job.

Accordingly, greater emphasis is placed on persistent and economically meaningful changes in the five regime shares across time and worker groups rather than on small movements in narrowly defined occupational categories.

A12. Occupation Share

Table A4 shows the share of employment for workers aged 15-64 in each two-digit occupation in 2011-12 and 2025. These occupation shares add up to the five regime shares in Section 3. The 2011-12 codes have been harmonised to NCO-2015.

Table A4: Employment Shares by Two-Digit Occupation, India, 2011-12 and 2025 (per cent)

ISCO-08 / NCO-2015	Title	2011-12	2025
11	Chief Executives, Senior Officials and Legislators	0.1	1.3
12	Administrative and Commercial Managers	1.1	0.6
13	Production and Specialized Services Managers	0.1	0.4
14	Hospitality, Retail and Other Services Managers	0	0.4
21	Science and Engineering Professionals	0.4	0.5
22	Health Professionals	0.3	0.6
23	Teaching Professionals	2.5	2.5
24	Business and Administration Professionals	1.1	0.8
25	ICT Professionals	0.3	0.7
26	Legal, Social and Cultural Professionals	0.3	0.7
31	Science and Engineering Associate	0.3	0.6
32	Health Associate	0.5	0.7
33	Business and Administration Associate	1	0.9
34	Legal, Social, Cultural and Related Associate	0.2	0.3
35	ICT Technicians	0.2	0.2
41	General and Keyboard Clerks	1	1.2
42	Customer Services Clerks	0.3	0.4
43	Numerical and Material Recording Clerks	0.6	0.3
44	Other Clerical Support Workers	0.1	0.4
51	Personal Service Workers	3.1	2.4
52	Sales Workers	7.4	9.1
53	Personal Care Workers	0.5	0.2
54	Protective Services Workers	0.4	1.1
61	Skilled Agricultural Workers	28.9	29.5
62	Skilled Forestry, Fishery and Hunting Workers	2.2	0.4
63	Subsistence Farmers	0	3.9
71	Building and Related Trades Workers	5.8	3.5
72	Metal, Machinery and Related Trades Workers	1.9	1.8
73	Handicraft and Printing Workers	0.9	1.3
74	Electrical and Electronics Trades Workers	0.6	1.1
75	Food Processing, Garment, Related Trades Workers	5.5	4
81	Stationary Plant and Machine Operators	2	1.5
82	Assemblers	0	0.1
83	Drivers and Mobile Plant Operators	2.9	4.5
91	Cleaners and Helpers	1	1.8
92	Agricultural, Forestry and Fishery Labourers	17.5	7.7
93	Construction & Manufacturing Labourers	7.6	11.5
94	Food Preparation Assistants	0	0.2
95	Street and Related Sales and Service Workers	0	0.3
96	Refuse Workers and Other Elementary Workers	1	0.7

Note: Share of employment of workers aged 15-64, usual status (principal status + subsidiary status, ps+ss). Street and Related Sales and Service Workers (95) have no routine-intensity score and are not assigned to a regime. Columns may not sum to 100 because of rounding. Source: Authors' calculations.

References

- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in US wage inequality. *Econometrica*, 90(5), 1973–2016. <https://doi.org/10.3982/ECTA19815>
- Arias, O., Fukuzawa, D., Le, D. T., & Mattoo, A. (2025). *Future jobs: Robots, artificial intelligence, and digital platforms in East Asia and Pacific*. World Bank. <https://doi.org/10.1596/978-1-4648-2199-8>
- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>
- Autor, D.H. and D. Dorn (2013). *The Growth of Low-Skill Service Jobs and the Polarization of the U. S. Labor Market*, American Economic Review, 103(5), 1553–1597.
- Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020), “The Fall of the Labor Share and the Rise of Superstar Firms”. *Quarterly Journal of Economics*, 135(2), 645–709.
- Autor D., Rodchenko, T., Martin, J., Iscenko, Z., Strand, S., Pearl, D., and M. Ferere. (2026). *Does AI assistance enhance or erode expertise? Evidence from a three-month field experiment in patent drafting* NBER Working Paper 35720.
- Bárány, Z. L., Patel, A., & Siegel, C. (2026a). *Does automation lower the labor share?* (CEPR Discussion Paper No. 21700). CEPR Press. <https://cepr.org/publications/dp21700>
- Bárány, Z. L., Patel, A., & Siegel, C. (2026b, August 5). Automation does not lower the labour share. *VoxEU.org*. <https://cepr.org/voxeu/columns/automation-does-not-lower-labour-share>
- Bentaouet Kattan, R., Macdonald, K., & Patrinos, H. A. (2018). *Automation and labor market outcomes: The pivotal role of high-quality education*, World Bank Policy Research Working Paper no. 8474. World Bank. <https://doi.org/10.1596/1813-9450-8474>
- Cazzaniga, M., Panton, A. J., Li, L., Pizzinelli, C., & Tavares, M. M. (2025). A gender lens on labor market exposure to AI. *AEA Papers and Proceedings*, 115, 56–61. <https://doi.org/10.1257/pandp.20251046>
- Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4), 1593–1640. <https://doi.org/10.1093/qje/qjx022>
- Deming, D. J., & Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *The Quarterly Journal of Economics*, 135(4), 1965–2005. <https://doi.org/10.1093/qje/qjaa021>
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702), 1306–1308. <https://doi.org/10.1126/science.adj0998>
- Fan, H., Hu, Y., & Tang, L. (2021). Labor costs and the adoption of robots in China. *Journal of Economic Behavior and Organization*, 186, 608–631. <https://doi.org/10.1016/j.jebo.2020.11.024>
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195–2217. <https://doi.org/10.1002/smj.3286>
- Giuntella, O., Lu, Y., & Wang, T. (2025). How do workers adjust to robots? Evidence from China. *The Economic Journal*, 135(666), 637–652. <https://doi.org/10.1093/ej/ueae086>
- Gope, D., & Gope, A. (2022). Students and academicians views on the engineering curriculum and industrial skills requirement for a successful job career. *Open Education Studies*, 4(1), 173–186. <https://doi.org/10.1515/edu-2022-0011>
- Hubmer, J., & Restrepo, P. (2026). Not a typical firm: Capital-labor substitution and firms’ labor shares. *American Economic Journal: Macroeconomics*, 18(2), 34–71. <https://doi.org/10.1257/mac.20230325>
- International Labour Organization. (2018). *Care work and care jobs for the future of decent work*. ILO.
- International Labour Organization. (2024). *World Social Protection Report 2024–26: Universal social protection for climate action and a just transition*. ILO. <https://www.ilo.org/publications/flagship-reports/world-social-protection-report-2024-26-universal-social-protection-climate>
- International Labour Organization. (2025a). *Generative AI and jobs: A refined global index of occupational exposure*, ILO Working Paper no. 140. ILO.
- International Labour Organization. (2025b). *Statistics on social protection: Proportion of population covered by at least one social protection benefit* [Data set]. ILOSTAT. Retrieved September 27, 2026, from <https://ilostat.ilo.org/topics/social-protection/>
- International Labour Organization. (2026). *Gen AI, occupational segregation and gender equality in the world of work* (Research Brief). ILO. <https://doi.org/10.54394/00033798>
- Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. *The Quarterly Journal of Economics*, 129(1), 61–103. <https://doi.org/10.1093/qje/qjt032>
- Karan, A., Negandhi, H., Hussain, S., Zapata, T., Mairembam, D., de Graeve, H., Buchan, J., & Zodpey, S. (2021). Size, composition and distribution of health workforce in India: Why, and where to invest? *Human Resources for Health*, 19(1), Article 39. <https://doi.org/10.1186/s12960-021-00575-2>
- Kuriakose, F., & Kylasam Iyer, D. (2018). Automation and the future of jobs in India, *India in transition*. Center for Advanced Study of India, University of Pennsylvania. <https://casi.sas.upenn.edu/iit/kuriakoseiye>
- Law, S. S. (2014). *A breakthrough in vocational and technical education: The Singapore story* (Vol. 43). World Scientific.
- Li, H., Ma, Y., Meng, L., Qiao, X., & Shi, X. (2017). Skill complementarities and returns to higher education: Evidence from college enrollment expansion in China. *China Economic Review*, 46, 10–26. <https://doi.org/10.1016/j.chieco.2017.08.004>
- Li, S., Whalley, J., & Xing, C. (2014). China’s higher education expansion and unemployment of college graduates. *China Economic Review*, 30, 567–582. <https://doi.org/10.1016/j.chieco.2013.08.002>
- Mahambare, V. (2023a). Get ready for a whole new future led by AI technology. *Mint*, January 10.
- Mahambare, V. (2023b). Close the prestige gap to find takers for unfancied jobs. *Mint*, June 29.
- Mahambare, V. (2023c). Could AI diffusion affect global patterns of migration? *Mint*, January 24.
- Mahambare, V. (2024). Urbanization pressure: India’s housing policy needs a big rethink. *Mint*, April 22.
- Mahambare, V., & Alam, A. (2026). Elusive jobs: How AI will

- demand even greater patience of India's unemployed youth. *Mint*.
- Mahambare, V., & Venugopalan, V. (2026). How to expand India's middle class in the age of AI: Appropriate skilling and job status elevation. *Mint*, June 15.
- Mahambare, V., Dhanaraj, S., & Sharma, S. (2021). India's New Employment Policy ought to focus on Young Adults. *Mint*, November 15.
- Mahambare, V., Munjal, P., Baruah, P., Gowthaman, N., & Mishra, A. (2026a). *Young adults at work in India*, Great Lakes Centre for Finance and Economics Research, GLCFER white paper series, No. 3.
- Mahambare, V., Srivastava, A., Gowthaman, N., Rammyaa, M., & Swetha Shree, R. (2026b). *Unlocking women's employment through safe housing: Lessons from Tamil Nadu's Thozhi hostels*, Great Lakes Centre for Finance and Economics Research, GLCFER white paper series, No. 4.
- Ministry of Human Resources and Social Security & Ministry of Civil Affairs. (2019). *Yanglao huiyuan guojia zhiye jineng biao zhun (2019 nian ban)* [National occupational skill standard: Elderly care worker (2019 edition)]. https://mzj.wuhan.gov.cn/zwgk_918/fdzdgk/gysyjs/shbz/shfl/201910/t20191023_1000650.shtml
- Ministry of Labour and Employment. (2025). *Employment linked incentive scheme: Scheme guidelines*. Government of India.
- Ministry of Statistics and Programme Implementation. (2025). *Periodic Labour Force Survey: Annual report 2024–25, MoSPI*. Government of India.
- NASSCOM. (2024). *Data annotation: Billion dollar potential driving the AI revolution*. NASSCOM.
- NITI Aayog. (2018) *National Strategy for Artificial Intelligence*, Government of India, New Delhi.
- NITI Aayog. (2023) *Transforming industrial training institutes*. Government of India
- NITI Aayog. (2026). *Reimagining care: Strategies for empowering caregivers in Viksit Bharat@2047*. Government of India
- Pizzinelli, C., Panton, A. J., Mendes Tavares, M., Cazzaniga, M., & Li, L. (2023). *Labor market exposure to AI: Cross-country differences and distributional implications* (IMF Working Paper No. 2023/216). International Monetary Fund. <https://doi.org/10.5089/9798400254802.001>
- UNESCO-UNEVOC. (2026). *TVET country profile: Germany*. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training. Retrieved September 28, 2026, from <https://connect.unevoc.unesco.org/home/Dynamic+TVET+Country+Profiles/country=DEU>
- Unified district information system for education plus. (2025). *UDISE+ report 2024–25*, Department of school education and literacy. Ministry of Education, Government of India.
- United Nations Population Fund, & International Institute for Population Sciences. (2023). *India ageing report 2023*. UNFPA India.
- Vashisht, P., & Rani, N. (2019). *Automation and future of garment sector jobs: A case study of India*, Working Paper 385, Indian Council for Research on International Economic Relations, New Delhi.

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