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India's Jobs in Transition:

Skills, AI and the Future of Work

Ayesha Ahmed, Kanika Mahajan, Anisha Sharma, Mansi Wadhwa

ABSTRACT

As India's working age population expands, the need to create productive and future ready jobs at scale is pertinent. This report maps employment growth in India between 2018 and 2025 using the Periodic Labor Force Survey with an eye towards illuminating occupation-level job growth patterns, the changing skill profile of the Indian workforce and exposure to AI developments. Overall, we find that employment has expanded since 2018, though much of the increase was in agricultural self-employment and low-skill nonfarm occupations. Our analysis provides evidence for job polarization - job growth was concentrated in low-skilled occupations coupled with modest growth in some high-skilled professional roles, with relatively no growth in medium-skill jobs. High-skilled, cognitive occupations are most exposed to emerging AI applications. So far, employment growth has been pronounced at both ends of the AI-exposure range. Manual, low-skill jobs, which are least-exposed to AI grew tremendously while high-skilled job grew to a lesser extent, resulting in the missing middle and echoing the broader polarization of the labor market. These findings draw policy attention towards the need for industry-relevant skills that enhance productivity and boost the AI-adaptability. Building data infrastructure that captures evolving worker and job characteristics is important to produce timely and relevant evidence that supports policy in times of technological change.

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CREDIT STATEMENT

This report was produced by a research team at the Isaac Centre for Public Policy, Ashoka University. Mansi Wadhwa contributed to the design, execution and drafting of the report, while overseeing data analysis and synthesis of findings. Kanika Mahajan and Anisha Sharma contributed to the design, execution, synthesis and drafting of the report. Ayesha Ahmed conducted data analysis, data management and provided excellent research support.

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INTRODUCTION

India is entering a decisive decade for jobs. By 2036, nearly two-thirds of its population will be of working age (ILO, 2024).[1] Realizing this demographic dividend depends on creating not just enough work, but productive, better-paid and future-ready work. This distinction matters because while rising employment can reflect expanding labour demand in dynamic sectors, it can also reflect distress-driven entry into low-productivity self-employment. The central question is, therefore, not just how many jobs India is adding, but what kind.

This report maps where employment has grown in India between 2018 and 2025, using seven waves of the Periodic Labour Force Survey (PLFS).[2] It identifies the sectors and occupations that have grown the fastest, examines the changing skill profile of the workforce, and tracks real wage movements. It also links Indian occupational data to two prominent AI-exposure indices to provide early evidence on which jobs, industries and regions are more exposed to current AI capabilities. Throughout, the report treats employment growth as a signal that must be interpreted carefully: for wage workers, employment and wage growth together provide a stronger indicator of the demand for skills, while shifts in self-employment are read with more caution.

We find that India is creating work, but the pattern of job creation remains uneven. Employment has expanded since 2018, yet much of the increase has occurred in agricultural self-employment and low-skill nonfarm occupations. Services have created a large number of jobs and remain the strongest engine of nonfarm employment growth, but the sector spans both high-productivity professional work and low-wage informal work. Manufacturing and construction have added workers, but not on a scale large enough to drive structural transformation away from agriculture. Meanwhile, India is seeing a form of job polarization: employment growth is concentrated among low-skill occupations and a smaller set of high-skill professional roles, with weaker expansion in medium-skill work.

The arrival of generative AI has added a new and fast-moving force to this transition. The stakes are particularly high for India, where millions of young workers are now entering the labour market, many in service-sector jobs where AI tools are most widely used. To assess the impact of AI on job growth during 2018-25, we link Indian occupations to leading AI-exposure indices (Felten et al., 2021; Eloundou et al., 2024) and observed AI usage through the Anthropic Economic Index. Exposure is concentrated in high-skill, cognitive occupations rather than in manual work. Employment growth, however, has been strongest at both ends of the exposure range — among the least-exposed manual jobs and the most-exposed cognitive ones — and weakest in the moderately exposed middle, echoing the broader polarization of the labour market. Our findings suggest that, so far, greater AI exposure has not gone hand in hand with job losses, as even the most-exposed occupations have continued to add jobs. However, adoption is still early and capabilities are advancing rapidly, so the same occupations could look very different within a few years. Building the evidence base to track this transition as it unfolds is an urgent priority.

Our findings have important implications for skilling and industrial policy. With declining education wage premiums, a narrow focus on delivering education credentials will not be enough. Workers also need industry-relevant, transferable skills to raise productivity, especially in low-skill jobs, and the ability to use new AI tools in exposed occupations. The report also points to a data gap: to measure AI and technology exposure and design skilling policy accurately, India needs better occupation-task-skills data, comparable to the US-based O*NET survey that captures occupation-specific worker and job characteristics, but built for the Indian labour market.

Key takeaways:

- **Jobs are rising, but structural transformation remains slow.** Working-age employment rose from 47% to 56.2% between 2018-2025 with almost 10.4 crore jobs added. However, over 4 crore workers entered agriculture, leaving it the largest sector providing employment in the country.

- **Services are the main non-farm engine, but job quality is uneven.** The sector added about 3.3 crore workers, with strong growth in trade and repair, accommodation and food, information and communication, and health and social services. However, service sector jobs span both high-productivity professional work and low-wage informal work. Manufacturing and construction each added 1.2-1.6 crore workers, which is not enough to shift the employment structure.

- **Self-employment drives a large part of recent job growth**. Almost the entire increase in agriculture is in self-employment. Of about 6.2 crore nonfarm jobs added, almost 2.4 crore came through self-employment and about 3.8 crore through wage employment.

- **Job growth is polarized, and the middle is missing.** Looking at wage employment, which is a better signal of labour demand, we find that job growth is concentrated at the two ends of the skill distribution, and strongest at the bottom. The fastest growth is in low-skill wage jobs such as mining and construction labourers (1.48 crore), cleaners, helpers and food-preparation assistants (47 lakh), while selected high-skill occupations—business, finance and sales professionals (27 lakh), and software, database and network professionals (24 lakh)—also expanded. The missing middle is therefore the central labour-market concern since not enough of the medium-skill jobs that support upward mobility are being added.

- **Wages point to a skills mismatch.** Professionals saw median real wages rise by 22.6%, while technicians and associate professionals saw a decline of about 20%, pointing to a potential mismatch between the skills demanded and those supplied. At the same time, the education wage premium is falling, suggesting that credentials alone are not delivering the skills valued by the market.
- **AI exposure is highest among skilled, cognitive occupations, but job growth tracks exposure unevenly.** The most AI-exposed occupations include software and database professionals, numerical clerks, mathematicians and actuaries, business and finance professionals, and associate professionals. The least exposed include mining and construction labourers, cleaners, food-preparation assistants, welders, and building workers. Crucially, worker shares rose most in the bottom 20% of AI-exposed occupations (1.2-1.6 p.p.) compared with only 0.6 p.p. in the top 20%, while moderately exposed occupations saw little to no growth.

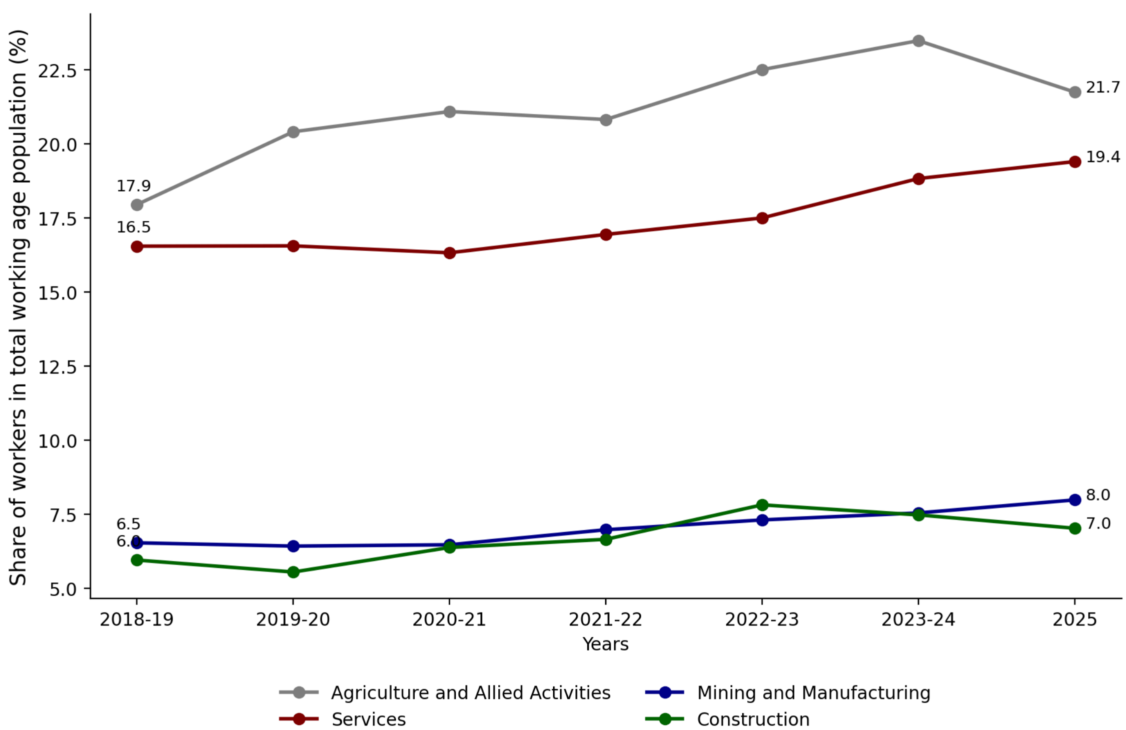
I. WHERE DOES INDIA WORK?

Sectoral breakdown of employment growth in India (2018-2025)

Overall, workforce participation as a percentage of India's working age population (between the ages of 15 and 59) has increased substantially from 47% in 2018-19 to 56.2% in 2025.

However, a sectoral breakdown of employment among India's working age population reveals that the agricultural sector continues to be the largest employer, followed by a steadily but slowly growing services sector. Nearly 21.7% of India's working age population worked in agriculture and allied industries in 2025, an increase by 3.8 p.p. since 2018 (Figure 1).[3] Services are the second biggest employer – 16.5% worked in the services sector in 2018-19 which increased to 19.4% in 2025. Construction and manufacturing each employed 7 to 8% of the working age population in 2025, fairly similar to their contribution to employment seven years ago.

Figure 1: Sectoral break-down of Indian workforce



Notes: *The figure plots sectoral workforce participation rates. Manufacturing includes national industrial classification codes for mining, manufacturing, printing, energy, and waste. Workforce is calculated using the current weekly status (ages 15-59).*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Growth in wage- and self-employment

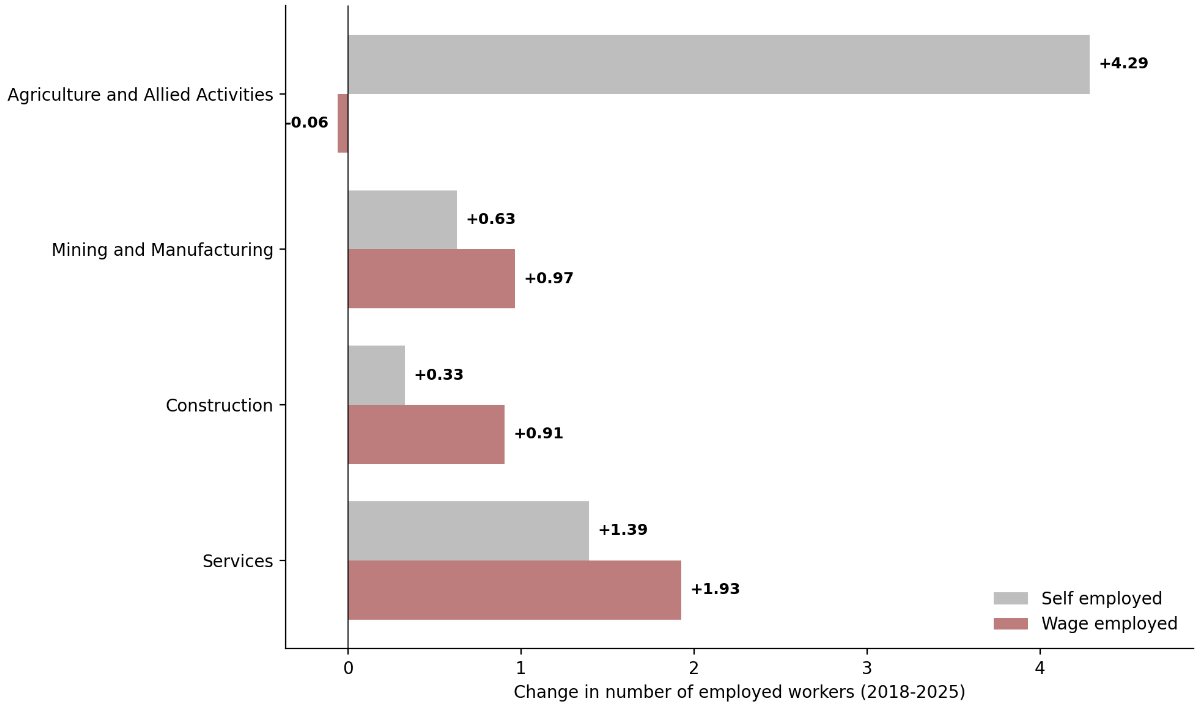
Within each sector, labour comprises wage-workers and self-employed workers. Wage workers include those who receive a regular salary (salaried work) or daily wages (casual work). Self-employed workers are those who operate their own farm or nonfarm enterprises. In 2025, 64.5% of all nonfarm workers in India received wages, either in salaried positions or through casual work (wage-employed), while the remaining 35.5% were self-employed. Figure 2 depicts sectoral growth in employment between 2018-19 and 2025, split by self-employed vs. wage workers.

The agricultural sector has witnessed the most growth, with 4 crore jobs added between 2018-19 and 2025, but almost all of these jobs have been in self-employed work. Self-employment in India is often regarded as low-productivity since it is low-paying, with earnings barely above casual labour and far below salaried employment (NCAER, 2025).[4]

The service sector added over 3.3 crore jobs over this seven year time period with a more even split by self- and wage- employment (58% of these new service workers were in wage employment). Construction and manufacturing sectors each added 1.2 and 1.6 crore jobs, between 2018-19 and 2025, respectively, of which about 90 lakhs to 1 crore jobs were in wage employment. In sum, except for agriculture, all sectors have witnessed a larger increase in wage employment as compared to self-employment.

These patterns suggest that rising employment in India does not necessarily imply growth-enhancing structural transformation. Development typically requires labour to move from low-productivity agriculture and informal work into higher-productivity nonfarm sectors and more stable wage employment (McMillan & Rodrik, 2011),[5] which is necessary to increase growth and improve wages (Amirapu & Subramanian, 2015;[6] Hasan & Molato, 2019;[7] Hasan et al. 2013,[8] ICPP, 2025[9]). However, India's recent pattern is more mixed: agricultural employment has expanded rather than contracted, partly through women's self-employment and unpaid or low-paid work (ICPP,2025; Deshpande,2025[10]). Additionally, a large proportion of service-sector jobs are in less-productive self-employment. Higher workforce participation in India since 2018 does not necessarily indicate productive labour reallocation.

Figure 2: Employment growth (2018-2025) : By industry and type of work



Notes: *The graph plots the increase in the number of employed workers in each sector between 2018 and 2025. Manufacturing includes mining, manufacturing, printing, energy, and waste. Employment is as per the current weekly status (age 15-59). Wage-employed includes salaried and casual workers. Changes are in crores.*

Source: *Periodic Labour Force Survey (2018-19 to 2025). Census population projections are used to estimate absolute numbers from survey calculations.*

Box 1: NCO concordance at the 3-digit level

To enable consistent longitudinal analysis across all rounds of the Periodic Labor Force Survey (PLFS), we harmonized occupational data across survey waves. PLFS identified occupations using the National Classification of Occupations 2004 (NCO-2004) in all the waves up till 2020-2021 and transitioned to the National Classification Of Occupations 2015 (NCO-2015) in all the rounds beginning 2021-2022. The official mapping between NCO 2004 and its 2015 counterpart was at the 6-digit occupation level but the PLFS identifies occupations of respondents at the 3-digit level. Therefore, a new concordance at the 3-digit level had to be constructed such that the occupations in the PLFS from the NCO 2004 rounds could be mapped to the NCO 2015 classification. We did this by first identifying direct matches of NCO codes and then using proportion-based reassignments for categories that were split in the new classification. For the remaining cases, we manually coalesced related occupational groups into newly aggregated categories. Throughout the process, the guiding principle was to preserve the fundamental skill hierarchies as much as possible. The end result is a unified, harmonized concordance that provides a unique mapping between the NCO-2004 and NCO-2015 at the 3-digit level, allowing one to seamlessly track occupational trends across all years of the PLFS. More specifically, all 3-digit occupations in the PLFS waves of 2018-2019, 2019-2020, and 2020-2021, which used NCO 2004, now conform with NCO 2015. Researchers and general public can download this concordance to use from Github.[11]

II. SKILLS, OCCUPATIONS AND WAGES IN THE NONFARM SECTOR

Next, we examine changes in the occupational and skill composition of India's workforce during 2018-2025. Skill levels of the workforce can be measured in several ways - using the hierarchical structure of the standard occupational classification, using educational attainment as a measure of acquired skill, and using wages as a proxy of how skills are valued in the labor market.

In this section, we use the National Classification of Occupations 2015 (NCO, 2015) to discuss skills distribution of the Indian workforce.[12] The analysis focuses on the nonfarm sectors of the economy, given our broader objective of understanding which occupations and skills are expanding outside agriculture and how these shifts can support structural transformation of the Indian economy.

Skill profile based on occupations

At the highest tier, the NCO-2015 classification organizes occupations into nine broad occupational divisions labelled by 1-digit codes. At the most granular level, each occupation is identified by a 6-digit code. 1-digit occupational divisions represent a hierarchy of skill levels required to work in corresponding occupations and are often used in the policy discourse to examine the skill profile of the workforce. Of the nine occupational divisions, the first three (1-Managers, 2-Professionals and, 3-Technical/Associate Professionals) typically represent high-skill job roles. The next three occupations (4-Clerks/clerical support workers, 5-Service and Sales Workers, and 6-Skilled Agricultural, Forestry and Fishery Workers) make up medium-skill workers and the last three (7-Craft and Related Trades Workers, 8-Plant and Machine Operators, and Assemblers, and 9-Elementary Occupations) form the low-skill workforce in India (Lewandowski et. al., 2022; NCAER, 2025[13]). Since the sixth division primarily reflects workers in the agricultural sector, we drop this category from the analysis that follows.[14]

The PLFS identifies occupations of respondents using 3-digit NCO codes. For each PLFS respondent, we are able to observe the 3-digit occupational group in which they work. While early PLFS rounds used the NCO-2004 to identify occupations of respondents, the latest PLFS rounds use NCO-2015. The concordance between the two NCO classifications is available only at the 6-digit level, and so we create a concordance between NCO-2004 and NCO-2015 at the 3-digit level. We discuss the concordance in Box 1 and make this concordance publicly available for use by the wider research and policy community.[15]

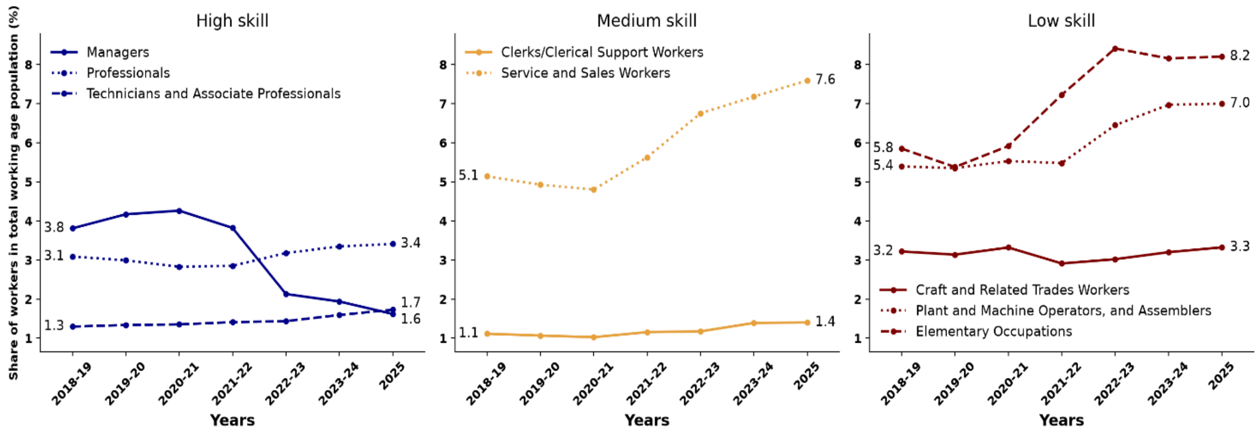
Box 2: Self-employment in PLFS

Individuals who operate their own enterprises are classified as self-employed in the PLFS. There are three types of self-employed workers in the PLFS: own account workers (who run their enterprises independently without hiring paid labour), employers (who hire paid labour for the operation of their enterprise) and unpaid household helpers (usually members of the family who help run operations without any monetary remuneration). Measurement issues complicate the analyses of wages for self-employed workers in the PLFS. Their remuneration comprises two parts – the profit earned from the enterprise and the monetary compensation for labour. It is difficult to separate the two in the data, especially in the absence of separate questions asking respondents about enterprise revenue and costs.

Much of self-employment in India tends to involve low-productivity own-account work by individuals who operate small enterprises. Own-account workers make up a large share of self-employed workers but their real earnings, on average, are modest. Of the self-employed, 76% were own-account workers in the non-farm sector while 57% were in the farm sector. Their average daily earnings (in real terms) were ₹427 and ₹327 respectively. The proportion of employers among the self-employed is far smaller in both the nonfarm and farm sectors (7.3% and 2.6% respectively). Employers tend to operate bigger and more productive enterprises, as reflected in a much higher real daily wage of ₹961, on average, in nonfarm enterprises and ₹556 in farm enterprises. The small share of relatively high-paid employers reflects the concentration of the self-employed in low-productivity work. Even those who are employers mostly run small enterprises – 87% of employers operate enterprises with fewer than 10 workers. Recent work demonstrates that there has been an increase in proportion of self-employed workers between 2017 and 2024 as compared to salaried/casual workers but the wages of self-employed workers have remained stagnant (NCAER, 2025).

A total of 30 crore individuals worked in the nonfarm sector in India in 2025 amounting to nearly 34.4% of the working age population. As illustrated in Figure 3, 18.5% of the working age population was in low-skill nonfarm employment (almost half of the nonfarm workforce), dominated by elementary occupations (8.2%) which involve simple tasks requiring physical effort.[16] Such jobs include cleaners, labourers, food preparation assistants, street and sales workers, and refuse workers.

Figure 3: Changing skill composition based on occupations



Notes: *The figure plots workforce participation rates across 1-digit occupation divisions. Skill is defined as per the NCO-2015 classification. Employment is as per the current weekly status (age 15-59). We include both wage and self-employed workers in the nonfarm sector.*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

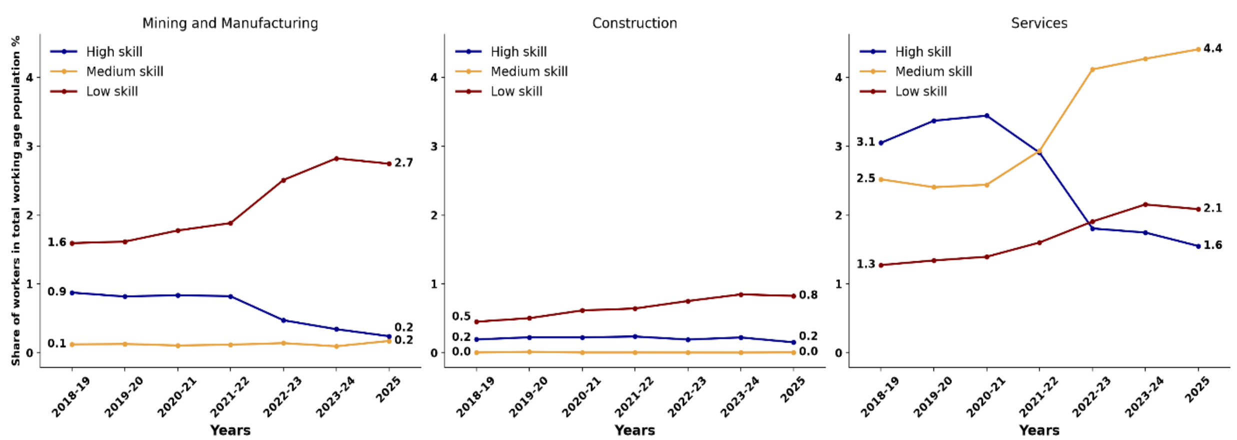
The size of the medium-skill nonfarm workforce was nearly half that of the low-skill workforce – in 2025, 9% of the total working age population was employed in medium-skill occupations as compared to 18.5% in low-skill occupations. Most of the medium-skill workers (7.6%) were in service and sales. These workers provide personal services (in retail, wholesale or shops) and in protective services.

In comparison, only 6.7% of the working age population was employed in high-skill jobs in 2025, with professionals making up half of this category (3.4%). Professionals work to advance existing knowledge and apply technical or artistic concepts, across various fields such as health, science and engineering, teaching, business and administration, legal/social, and information and communication technology. Generally, these jobs require high levels of education and formal training and tend to be structured in formal enterprises. Technicians and Associate Professionals fall relatively lower on the skill hierarchy and are responsible for technical tasks pertaining to operations, government/business regulations, and application of concepts even though they work in the same fields as Professionals.

Figure 4: Sectoral skill composition: Wage workers vs self-employed

Figure 4A: Skill profile among wage-employed workers

Figure 4B: Skill profile among self-employed workers



Notes: *The figure plots sectoral workforce participation rates across occupation-based skill divisions. Manufacturing includes mining, manufacturing, printing, energy, and waste. Employment is as per the current weekly status (age 15-59). Wage-employed includes salaried and casual workers. The figure splits the non-farm working population into wage-employed and self-employed workers.*

Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Skill profile: By sector and type of work

Figure 4 shows the skill composition of each segment of the nonfarm sector (manufacturing, construction and services) of the Indian economy separately for workers earning wages (salaried or casual work) in panel A and workers who are self-employed in panel B.

Among the wage-employed, low-skill workers dominate both the manufacturing and construction sectors. Medium- and high-skill workers formed a very small share in both sectors in 2025, accounting for 20% of all workers in manufacturing and barely 3% of all workers in the construction sector. In recent years, both sectors have seen an increase in the share of low-skill workers while both medium and high skilled worker growth has stagnated. On the other hand, services tend to employ wage workers from all skill levels: the proportions of high-skill and medium-skill wage workers are around 36% each, the share of low-skill workers of total service workers was around 28% in 2025. In services, all the three categories of wage workers by skill have grown over 2018-2025.

Among the self-employed, we see different patterns. Manufacturing and construction employ large numbers of low-skill workers along with a sizable share of high-skill workers but almost no medium-skill workers. The share of high-skill self-employed workers was almost half as much as the share of low-skill workers in both the sectors in 2018. However, the high-skill share has fallen in recent years, and in 2025 high-skill workers were less than one-tenth of the low-skill workers in manufacturing and one-fourth in construction. Notably, the category that dominates high-skill self-employed workers in the country are managers (Figure A1). These are likely to comprise a significant number of small-manufacturing or construction unit owners who manage their own business, and the categorization of such workers into “high-skill” is debatable.

The service sector also employs a large proportion of the high-skill self-employed workforce in India. Notably, during 2018-2025, the proportion of the high-skill self-employed has fallen while medium-skill self-employed has increased by a similar amount. These trends are largely driven by the category of managers and could partly be explained by re-categorization of the managers into other occupations (we discuss this possibility in Box 3). In sum, across all the sectors there is a distinct decline in the high-skill self-employed, accompanied by either an increase in low-skill (manufacturing and construction) or both medium- and low-skill (services).

Box 3: Managers as an occupation

Managers are classified as a high-skilled occupational division (NCO 1) under the NCO-2015. Their responsibilities include directing, leading, and coordinating the activities of government or business entities, across a variety of sectors and seniority levels. This category captures managers working in large formal enterprises as well those in smaller unincorporated establishments and MSMEs across the country.

Over the last seven years, the share of managers in the nonfarm sectors declined substantially from 3.8% in 2018-19 to 1.6% in 2025, driven primarily by the decrease in self-employed managers (by 1.8 crores). This decline in self-employed managers started to take shape after the year 2021 while the share of Managers in wage employment remained steady during this period (Figure A2). In tandem, we find that self-employed managers in later PLFS rounds tend to be older and earn higher daily wages. The median real daily wages for self-employed managers increased by approximately 80% between 2018-19 and 2025. The average age of self-employed managers also increased after 2021, though no such trend was observed for managers in wage employment. Such compositional changes within the category of Managers indicate potential reclassification of managers into other occupations.

A likely contender for these occupations are Service and Sales Workers (NCO 5) employed within the service sector of the economy. Between 2018-19 and 2025, the share of self-employed Managers in the service sector declined by 1.6 percentage points and that of self-employed Service and Sales Workers analogously increased by 1.8 percentage points. (Figure A3). This decline in self-employed Managers is driven by a decline in own-account workers and helpers in household enterprises, while the share of Managers who are employers remains largely stagnant over this period. We find a parallel increase in own-account workers categorized as Service and Sales Workers during this period. It is plausible that workers who operate small self-owned establishments with no additional workers are no longer classified as Managers in the PLFS and instead are classified as own-account Service and Sales Workers after 2021.

Broad occupational growth: By type of work

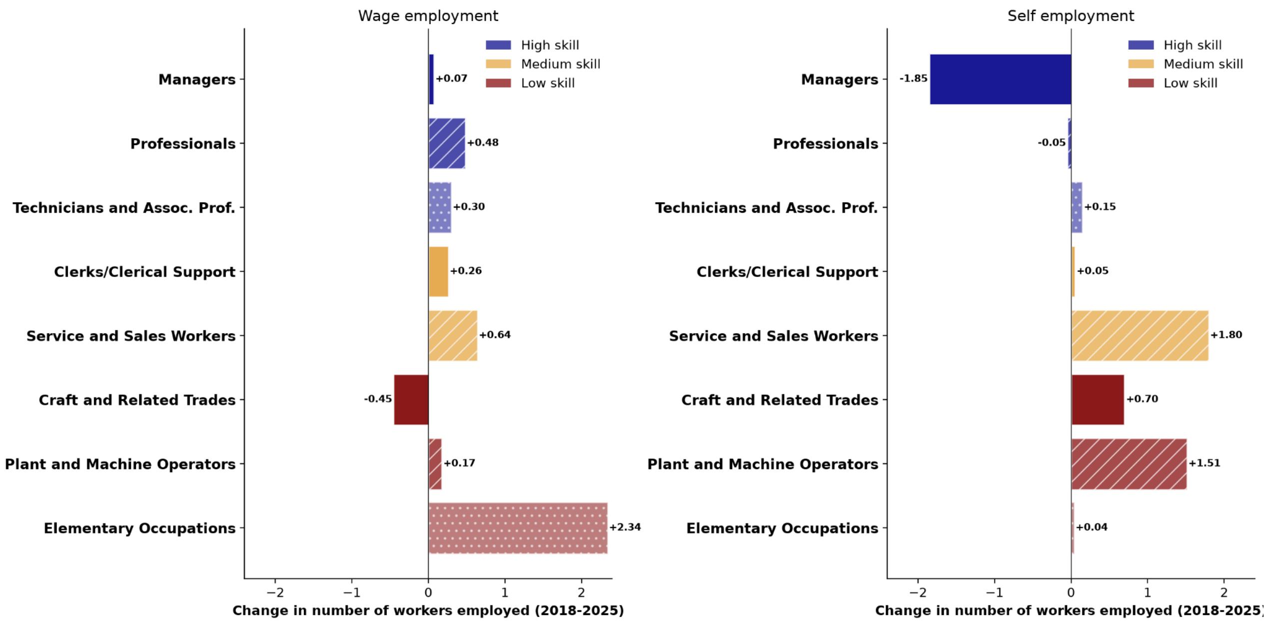
We now examine which 1-digit occupations across the skill spectrum have grown between 2018-19 and 2025 to understand where jobs are being created in the nonfarm sector. Several interesting findings emerge.

First, the number of wage workers increased by 3.8 crore while the self-employed increased by nearly 2.4 crore (Figure 5). Second, low-skill and medium-skill occupations in the nonfarm sector grew the most. In contrast, employment gains in high-skill categories were comparatively modest.

However, patterns differ distinctly across wage and self-employed workers. The increase in high-skill and medium-skill workers is almost comparable among wage workers at around 0.85-0.9 crores, while low-skill workers increased by almost 2.1 crores. On the other hand, there was a decline in self-employed high-skill workers with an increase in medium-skill and low-skill workers. This is driven by the category of self-employed managers, which have decreased by almost 1.85 crores, while services and sales workers have increased in the medium-skill category. This is in line with the decline we observed in the worker shares of high-skill managers, with a similar increase in medium-skill service sector workers. We discuss the decline in managers in Box 3.

We next turn to occupational growth patterns within each skill category. One of the fastest growing occupational divisions among the low-skill occupations was that of Elementary Workers, which grew from 5.8% to 8.2% of the working age population during 2018-2025 (Figure 3). Approximately 2.3 crore additional jobs were added in elementary occupations, of which almost all were in wage employment (Figure 5). Jobs in the other two low-skill occupational divisions (Craft Workers and Plant and Machine Operators) also grew but largely in self-employment: self-employed Plant and Machine Operators grew by 1.5 crore and Craft and Related Trades workers grew by 70 lakhs (Figure 5) but such large gains are not seen in wage work in these occupations. Figure A4 in the Appendix shows the change in levels over the years.

Figure 5: Growth in non-farm employment: By occupation



Notes: *The figure plots the change in the number of nonfarm workers at the 1-digit occupation level for the wage-employed (left hand side) and self-employed (right hand side). Wage-employed includes both salaried and casual workers. Skill is defined as per the NCO classification. Employment is as per the current weekly status (age 15-59). Change is in crores.*
Source: *Periodic Labour Force Survey (2018-19 to 2025). Census population projections are used to estimate absolute numbers from survey calculations.*

Growth in medium-skill occupations was driven by Service and Sales Workers, who grew substantially between 2018-19 and 2025. Service and Sales Workers employed in salaried or casual work grew by approximately 64 lakhs, but the growth in self-employed workers in this sector was three times as large (1.8 crores). Clerical occupations added approx. 30 lakh workers in total. However, as discussed earlier, much of the growth in medium-skill self-employment could be due to re-classification of occupations over time and not an actual change in skills or type of work.

Among high-skill occupations, Professionals and Technicians/Associate Professionals grew substantially, almost entirely in wage employment. 48 lakh jobs were added to Professional job roles and 30 lakh Technicians and Associate Professionals were added over the last 7 year period. Self-employment did not grow substantially in either of these occupations, likely due to the nature of these roles which require formal enterprises and structured employment contracts. However, Managers are an exception among high-skill occupations both with regard to the nature of their job role and their growth trajectory in the last 7 years. We observe a decline in workers classified as Managers in self-employment by 1.8 crores (see Box 3 for more).

Taken together, the above patterns indicate that within self-employed workers there is an increase only in low-skill workers while high- and medium-skill workers have not changed over this period. Some growth has occurred in high-skill wage workers. However, this has been less than the growth in low-skill wage workers.

Real wage growth for wage workers

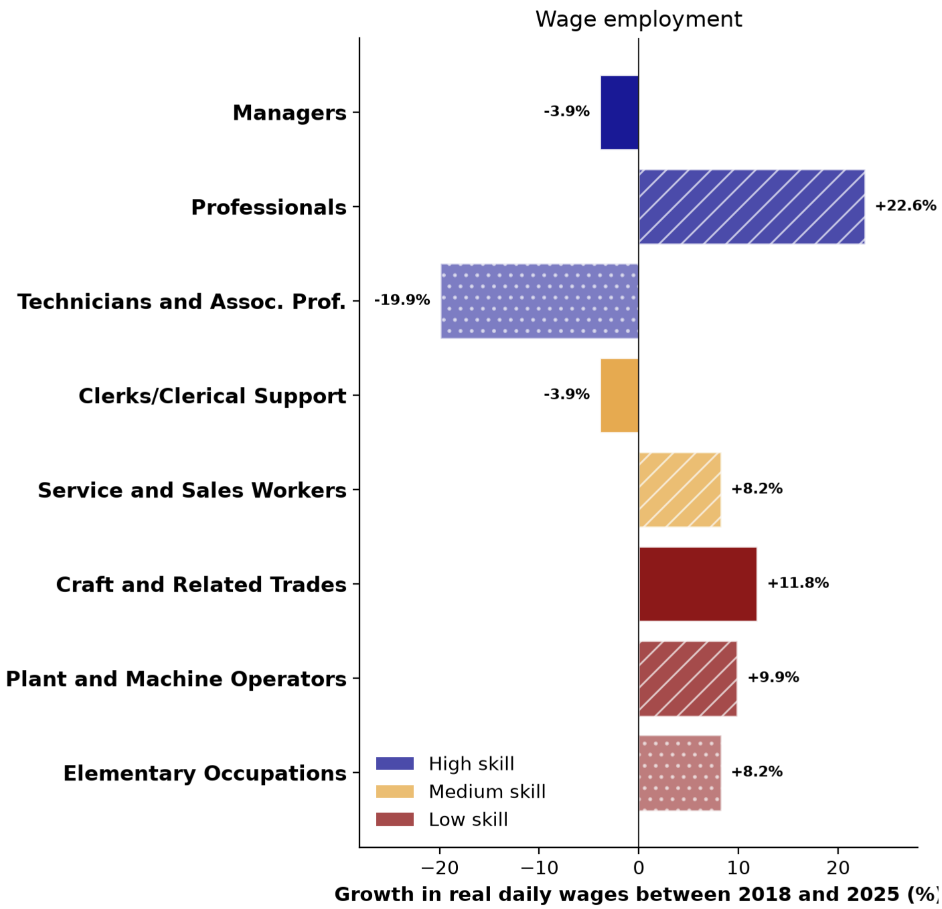
In this section, we examine growth in real wages across occupations for the wage workers over the last 7 years.[17] Apart from job growth, changes in real wages can be another indicator of changes in occupation-specific relative demand, as compared to supply, or occupation-specific productivity changes in the economy.[18]

The computation of wages in PLFS data for self-employed workers is less reliable than for wage-employed workers. For salaried and casual workers, the pre-tax gross remuneration is available in PLFS. However, for self-employed workers, complications arise in distinguishing the profit earned by the enterprise from the payment to individuals for their labour, making it difficult to analyze self-employment income. Box 2 discusses these issues in more detail. Moreover, in order to reap the demographic dividend and employ Indian youth productively, the focus must be on creating not just any jobs, but 'good jobs' characterized by high-productivity, higher wages and access to social protection. Therefore, we focus on wage growth across occupations for wage-employed workers.

Real wages have risen markedly for high-skill professionals, while medium- and low-skill occupations have seen more modest increases. During 2018-2025, median real daily wages among Professionals increased by 22.6%, rising from ₹758 in 2018-19 to ₹929 in 2025 (Figure 6). In terms of wage growth, Professionals surpassed all other occupational categories in the last seven years.

At the same time, wages of the other two high-skill groups decreased during this time period. The real wages of Technicians and Associate Professionals decreased by 20%, potentially indicating structural technological changes driven by AI and other technologies, leading to a lower demand for workers. The real wages for managers have also fallen slightly over time.

Figure 6: Real wage growth across broad occupational divisions



Notes: *The figure plots the growth in real daily wages between 2018 and 2025 for nonfarm wage employed workers which includes both salaried and casual workers. Skill is defined as per the NCO classification. Daily wages are based on the daily status (age 15-59) and the levels are median values. The unit is ₹.*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Real wage growth among medium- and low-skill workers was more moderate in comparison. Despite tremendous growth in the number of workers employed in the medium-skill Service and Sales occupations, their real wages increased only by 8.2% (about 1% per annum). The median worker in this occupational division earned ₹303 per day in 2018-19, which increased to ₹328 in 2025. Across all three low-skill occupational divisions, real wages grew between 8 and 12% over the seven year period. Interestingly, the growth in wages was the smallest for Elementary occupations which added the most jobs across the economy during this time period. Figure A5 in the Appendix shows the changes in wage levels over the years.

The slow wage growth in low-skill occupations could reflect push factors leading to a relative increase in the supply of low-skill workers, along with greater demand in these sectors. On the other hand, increase in both real wages and total jobs of professionals indicates a robust growth in demand for such jobs relative to supply of labour. Within the high-skill occupations, the ones higher on the skill spectrum are increasing both in real wages and employment, showing that these jobs might form an important fulcrum for high-productivity employment growth in the country.

III. SKILLS, JOB POLARIZATION AND THE EDUCATION PREMIUM

Measuring skill levels in the Indian labour force: Another approach

We next turn to tracking occupation-specific job growth by a more granular measure of skills.

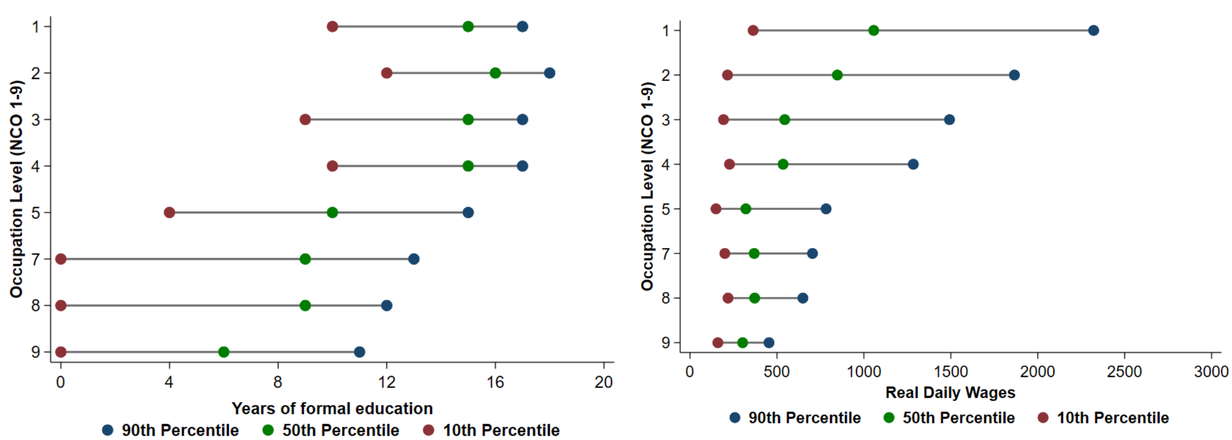
Previous sections relied upon the skill classification implicit in the NCO-2015 classification based on the hierarchy of 1-digit occupation codes. As such, we classified occupational divisions 1-3 as high-skill, 4-5 as medium-skill and 7-9 as low-skill. However, the skill distributions of workers across these broad 1-digit occupations overlap considerably. In particular, several workers in occupations classified as medium-skill are closer to either high-skill or low-skill occupational groups.

Here, we take a more empirically grounded approach to skill measurement by using occupation-specific baseline years of formal education and baseline real daily wage rates, measured in 2018-19, as proxies for the skill content of occupations. While education levels indicate skills acquired through formal channels, real wages reflect how each worker's skills are valued in the labour market. We then measure the changing demand for workers based on these alternative skill measures over the past seven years.

We find that these two methods of measuring skills – years of formal education and wages – produce broadly similar rankings of occupations based on their skill content (Figure 7). The left panel of Figure 7 depicts the distribution of educational attainment for each of the 9 NCO occupations for wage-employed workers in the nonfarm sector of the economy. The green point represents median years of formal education among workers in that sector while the red and blue points represent the 10th percentile and 90th percentile years of education, respectively. High-skill occupations (NCO 1, 2, 3), on average, have higher median years of formal education than others. The overall distribution of years of formal education for high-skill occupations is farther to the right of the graph in comparison to other occupational divisions. Medium-skill occupations (NCO 4 and 5) and low-skill occupations (NCO 7, 8, 9) have lower median years of formal education. Occupation 4 (clerical support) appears closer to high-skill workers while Occupation 5 (Service and Sales) is closer to the upper end of the low-skill workers, as expected.

The right hand panel of Figure 7 shows the distribution of real daily wages for each of the 1-digit NCO divisions calculated in a similar way. High-skill occupations (NCO 1, 2, 3), on average, have higher median real wages and a wider distribution that is skewed to the right by some high-earning occupation categories. Medium-skill occupations tend to have narrower wage distributions and comparatively lower median real wages. Low-skill occupations have the lowest median real wages and workers in these occupations tend to be heavily concentrated towards the lower end of the income-distribution. Again, Service and Sales workers (NCO 5), which are a part of medium-skill occupations, are closer to the low-skill occupations. Figure A6 in the Appendix repeats this analysis for self-employed workers in the nonfarm sector. It shows that the skill categorizations based on NCO vs education/wage based measures are less consistent with one another in the case of self-employed workers.

Figure 7: Distribution of educational attainment and wages for NCO-1 digit occupations



Notes: *The figures plot a range from the 10th to the 90th percentile of years of education and real daily wages for each of the occupational divisions in the NCO representing the nonfarm wage employed workers. Category 6 is excluded from the graph since it largely comprises agricultural occupations. Daily wage calculations are based on the daily status (age 15-59) and the unit is ₹.*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Fastest growing 3-digit occupations

In this section, we highlight the occupations, captured more granularly at the 3-digit NCO level, in which employment increased the most between 2018 and 2025. Figure 8 depicts occupational growth across skill levels, where the skill content of occupations is based on years of education. Workers with eight or fewer than eight years of formal education are categorized as low-skill, between more than eight and fewer than fourteen years of formal education are categorized as medium-skill, and those with fourteen or more years are categorized as high-skill. We focus on years of education since this is likely to be less noisy and more precisely measured than real daily wages. For comparison and consistency with the previous sections of this report where we measure skills using the NCO classification, we also show the same increases using the

NCO-based skill classification in Figure A7 in the Appendix. We find that the list of topmost growing occupations is nearly identical in the two figures, regardless of how we define skill levels, and so we focus on Figure 8 here.[19] Table A1 in the Appendix displays the more granular occupation titles falling within these 3-digit occupation groups.

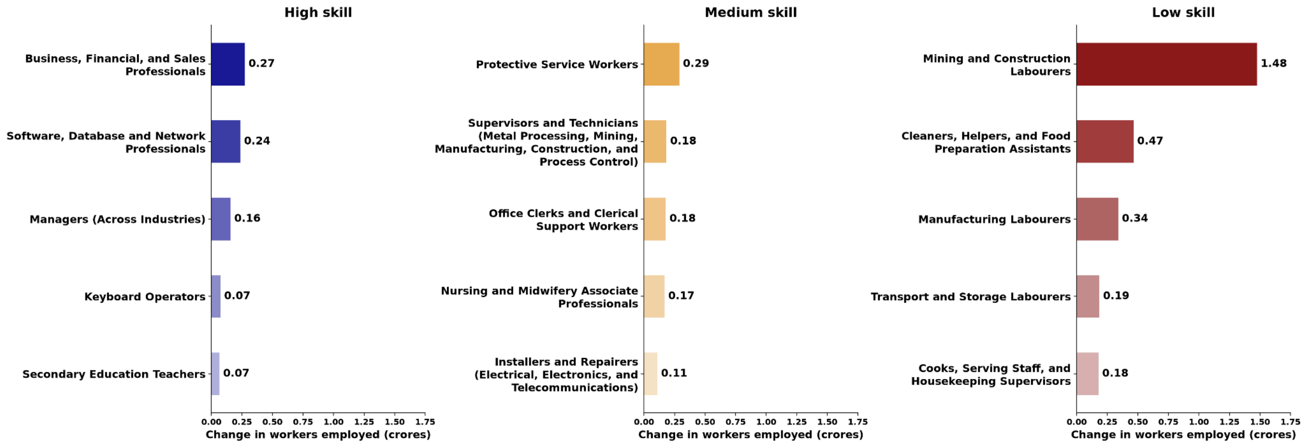
High-skill: Among high-skill occupations, the top growing roles are in Software, Database and Network Professionals (+24 lakh) and Business/Financial/Sales Professionals (+ 27 lakh). The former group includes occupation titles like software developers, web developers, application programmers and systems analysts and others who improve IT systems and develop digital technologies. The latter category includes financial services professionals, sales and marketing experts, and administration professionals. The third-fastest growing occupational group is Managers, which includes professionals undertaking general and production related management roles in a variety of nonfarm industries. Nearly 15.7 lakh managers were added between 2018 and 2025. Two other occupational groups grow through this period, though the magnitude of growth is much smaller. Keyboard operators, which include data entry clerks and typists, grew by 7.4 lakhs. Secondary education teachers grew by 6.7 lakhs.

Medium-skill: Protective service workers (which includes occupations such as police officers, fire fighters, personal security officers, and watchmen) were the fastest growing occupational group among medium-skill occupations, increasing by around 29 lakhs during this seven-year period. Supervisors and Technicians working in metal processing, mining, manufacturing, construction, and process control areas grew by 18 lakhs during this period. Two other occupational groups added workers at similar levels – Office Clerks and Clerical Support workers and Nursing and Midwifery Associate Professionals both added 17 to 18 lakh workers. Finally, nearly 11 lakh workers were added in the Installers and Repairers occupation group, which includes electricians, electronics servicers and installers.

Low-skill: Our analysis indicates that low-skill occupations have grown the most between 2018 and 2025. This growth is concentrated in the occupational group of Mining and Construction Labourers which have grown by around 1.48 crores during this period. Workers have also been added in other low-skill occupational groups, though at a much smaller scale. Cleaners, Helpers and Food Preparation Assistants have grown by 47 lakhs. Manufacturing Labourers increased by 34 lakhs. Fewer than 20 lakh jobs were added each in the categories of Transport and Storage Labourers as well as Cooks, Serving Staff and Housekeeping Supervisors.

Figure 8: Fastest growing occupations in India

(Skill classification based on education level)



Notes: *This figure shows the fastest growing 3-digit occupations (in terms of workers added) in the nonfarm sector among wage-employed workers (which includes both salaried and casual workers). Skill definition is based on years of formal education (<= 8 years is low-skill, between 8 and 14 years is medium-skill, and >= 14 years is high-skill). The change in number of workers employed is in crores.*
Source: *Periodic Labour Force Survey (2018-19 to 2025). Census population projections are used to estimate absolute numbers based on survey calculations.*

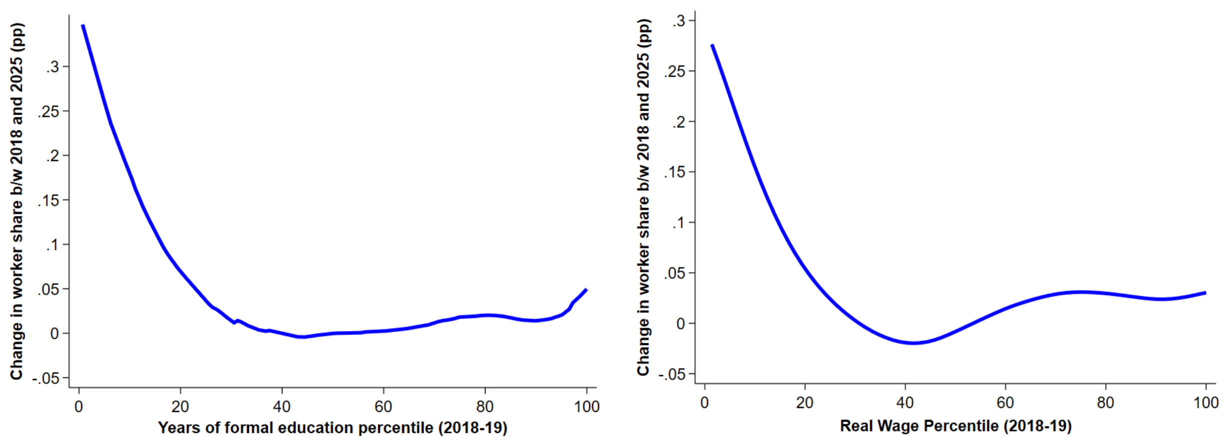
Skills and employment growth: Evidence of job polarization

In previous sections, when measuring skills using the NCO classification, we found that the growth in wage employment in the nonfarm sector has been the largest in the low-skill occupations (nearly 2 crore), followed by smaller increases in medium- and high-skill workers (85-90 lakhs).

We now examine patterns of employment growth using alternative measures of the skill content of occupations. Figure 9 plots 7-year changes in occupational worker shares against measures of baseline skills (occupation-specific formal education years on the left hand side and real wages on the right hand side as measured in 2018-19). We find evidence of job polarization in the Indian labour market: employment growth at both the lowest and highest ends of the skills spectrum coupled with a corresponding lack of growth in medium-skill jobs. The U-shaped curve with a long left tail indicates that worker shares rose most sharply among the lowest skilled occupations and somewhat modestly among high-skill occupations, but no growth was observed in the worker shares among the medium-skill job roles.

The phenomenon of job polarization has been observed around the world, with several countries experiencing a 'hollowing out' of medium-skill jobs owing to automation of routine tasks. Routine tasks are activities that are conducted by following set procedures and schema, which makes them easy to automate.[20] High-skill jobs typically comprise more non-routine cognitive tasks while medium-skill jobs involve more routine tasks that are amenable to automation through technological adaptation. Low-skill jobs tend to require manual effort and physical labour which is more difficult to automate (Acemoglu & Autor, 2011;[21] Goos et al., 2009 [22]). In the Indian context, the higher the skill level of a job, the fewer routine tasks that it incorporates (Khurana & Mahajan, 2020).[23]

Figure 9: Job polarization: Employment grows more at bottom and top ends of the skills distribution



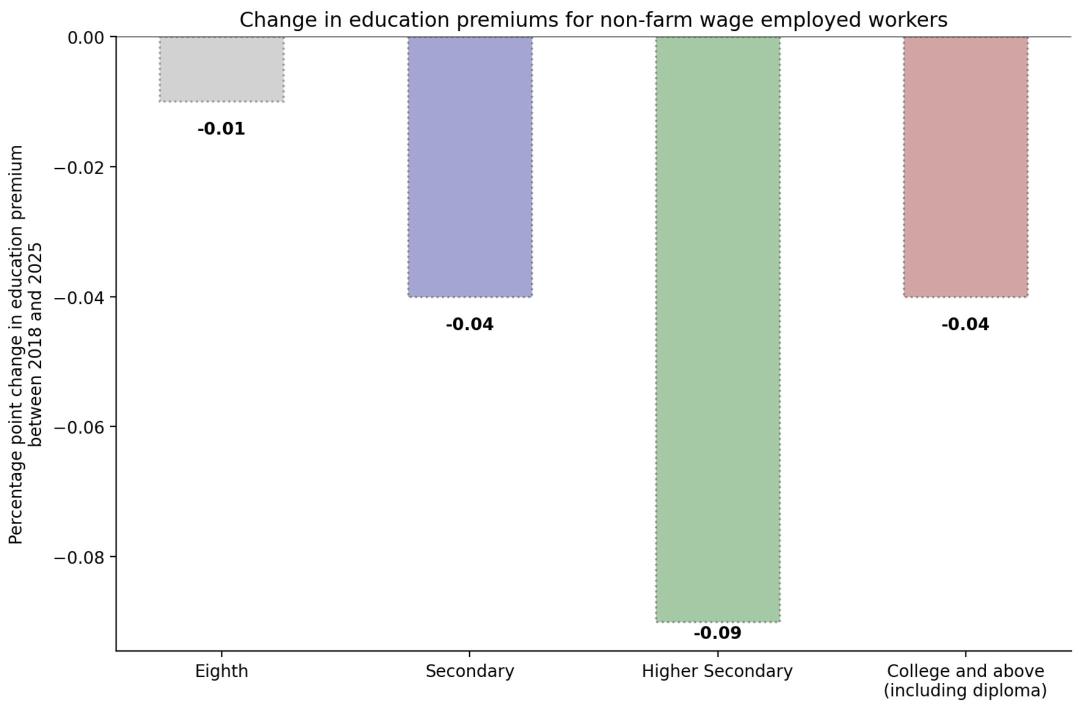
Notes: *The figure shows the change in nonfarm wage-employed worker shares across the skill distribution. The x-axis plots the percentile of formal years of education on the left and real daily wages on the right, and the y-axis plots the change in worker shares between 2018-19 and 2025. Daily wages are as per daily status (age 15-59). The smoothed line applies Locally Weighted Scatterplot Smoothing (LOWESS), a non-parametric method that reduces localized data noise and highlights the underlying trend.*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Changes in the wage premium for education

Given the job polarization observed between 2018-2025, we next ask if there was any change in the wage premium for education over time. If the increase in demand is the highest for the lowest skill occupations it is plausible that the education wage premium — the percentage increase in earnings that a worker receives for obtaining a higher level of education — in the labour market has fallen over time.

Using regression models that predict real daily wages for each level of education while controlling for a quadratic function of age, gender and industrial sector, we find that the education wage premium has declined for all levels of education between 2018 and 2025 (Figure 10). The decline in the wage premium is the largest for workers with higher secondary education. The wage premium for workers who completed Class 12 is 9 percentage points lower in 2025 than in 2018-19. The pattern is also true for college and diploma educated workers but to a lesser extent (4 percentage point decrease). This can indicate a supply-demand mismatch as more individuals complete higher education degrees without adequate job opportunities at these skill levels available to absorb them. Alternatively, the educational credentials for workers may not adequately embody the skills that are actually valued by the labour market, and this mismatch may be increasing over time. Figure A8 in the Appendix shows a plot of regression coefficients for education wage premiums for each year between 2018-19 and 2025.

Figure 10: Change in education premium



Notes: *The graph plots change in regression coefficients for education premiums for different levels of education over the span of 7 years for nonfarm wage-employed workers. The regressions control for a quadratic function of age, gender, and industrial sector. The reference category is workers who have not completed eighth standard including illiterates.*

Source: *Periodic Labour Force Survey (2018-19 to 2025).*

IV. ARTIFICIAL INTELLIGENCE AND THE INDIAN LABOUR MARKET

Recent advances in artificial intelligence (AI) have generated significant debate about the implications for employment and the future organization of work. AI technologies have so far been successful in conducting tasks related to text and image processing, speech, coding, data analysis, and other technical tasks. This has led to considerable concern about the labour market impacts of the diffusion of AI, as firms may potentially replace human workers with AI agents, especially in the high-skill occupations. At the same time, AI also has the potential to increase worker and firm productivity, leading to an increase in demand for some jobs.

We examine these questions in the context of the Indian labour market by combining PLFS data with prominent AI exposure indices that rank occupations on the basis of their exposure to AI technologies. In particular, we use AI exposure indices developed by Felten et al. (2021)[24] and Eloundou et al. (2024)[25] since we find them to be more relevant for the Indian labour market. Box 4 discusses different AI exposure indices and the challenges of measuring AI exposure by occupation in the Indian context. We then check exposure against actual adoption using the Anthropic Economic Index (2026),[26] which measures observed AI usage at the occupation level. Unlike the Felten and Eloundou indices, which measure AI's theoretical ability to perform tasks, the Anthropic index captures how AI is actually being used today.

Box 4: Measuring AI exposure: Indices and gaps

Several indices capture the exposure of jobs to AI, though they vary in how exposure is measured. Generally, AI exposure indices are created by (i) tracking the extent to which functions of a job can be executed by AI tools instead of humans and then (ii) aggregating exposure measured for each task/ability/function to the occupation-level. Prominent AI exposure indices include ones developed by Webb (2020), Felten et al. (2021), Chopra et al. (2025) and Eloundou et al. (2024).

Felten (2021) and Eloundou (2024) first analyzed the extent to which AI tools can carry out the functions of specific occupations. Felten does this using human coders who rate how well AI tools can match human abilities while Eloundou does this by rating how much faster occupation-specific activities and tasks can be done using AI tools, as assessed by both human coders and GPT-4. Exposure is measured for each occupational ability (Felten) and for each occupational task (Eloundou). Then, these measures are aggregated for each occupation. The Webb (2020) index matches the text of occupational task descriptions and the text of AI technology patents to quantify the overlap between AI tools and the task content of occupations. The index by Chopra et al. (2025) measures which skills are automatable by AI tools, based on specific tasks. All four indices use data from the US-based Occupational Information Network (O*NET), a repository of data about various attributes of occupations generated through worker surveys and expert reviews.

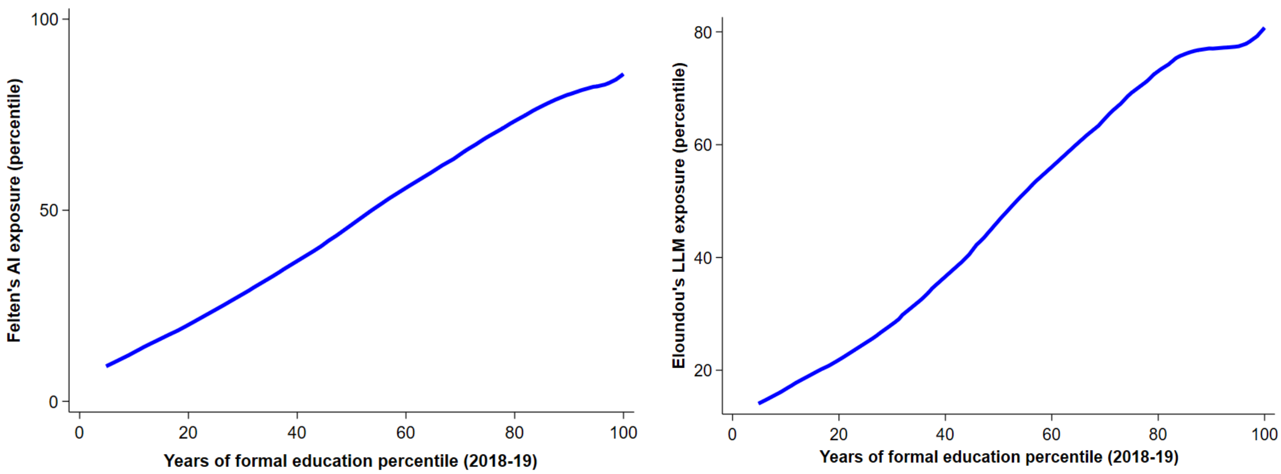
For the purposes of this analysis, we prefer the Felten (2021) and Eloundou (2024) indices because (i) they both estimate AI exposure based on how AI tools might carry out abilities or tasks embodied within occupations, (ii) both are valid measures used by the research community and (iii) both target AI capabilities primarily pertaining to language, images, coding, and speech. In the Indian labour market, these reflect the most likely uses of AI. Moreover, the index by Chopra (2025) is not publicly available for use and Webb (2020) index is likely to be outdated by now, given the rapid pace of AI development.

While these indices are useful measures of AI exposure, there are two caveats. First, while all indices use different ways of measuring exposure to AI, none of them predict the labour market impacts of AI. Instead, they measure the extent to which tasks and skills used within occupations overlap with the capabilities of AI tools. This means that they cannot be used to distinguish between occupations where AI tools complement human effort and where they can replace human workers. Second, new AI technologies are being developed at a fast rate and the current environment is dynamic. To what extent these indices represent future AI capabilities is unclear, as labour markets continually adapt to new technologies, and new tasks emerge and old ones get phased out.

Which occupations are more exposed to AI?

Figure 11 plots the two occupation-level AI exposure indices (Felten et al., 2021, and Eloundou et al., 2024) against the percentile of years of education for an occupation in the base year 2018-19.[27] It illustrates that high-skill occupations are the most exposed to AI capabilities, and, as Figure A9 shows, to AI usage as well. The two theoretical measures of exposure are closely aligned with real-world adoption: the Anthropic index has a correlation of 0.76 with Felten's index, and 0.84 with Eloundou's. The pattern is identical when we use real wage percentiles as a proxy for skill content (Figure A10). High-skill occupations that rely on cognitive capabilities of workers are more likely to include non-routine cognitive tasks that are more readily done by new-age AI tools. On the other hand, low-skill occupations (lower end of the base education and real wage distribution) encompass tasks that are not amenable to being automated by existing AI technologies.

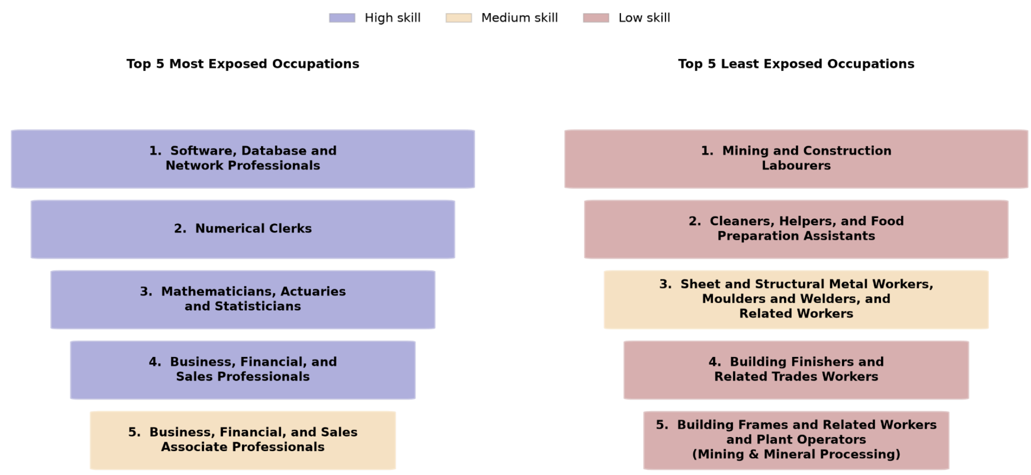
Figure 11: AI exposure and skills



Notes: *The figure plots AI exposure across the skill distribution (measured by years of formal education) for the nonfarm wage employed workers.The x-axis plots the percentile of years of formal education and the y-axis plots occupation-specific AI exposure for the two different indices. The smoothed line applies Locally Weighted Scatterplot Smoothing (LOWESS), a non-parametric method that reduces localized data noise and highlights the underlying trend.*
Source: *Periodic Labour Force Survey (2018-19 to 2025); Felten et al (2021); Eloundou et. al (2024).*

Figure 12 shows the most and least AI-exposed occupations that were identified by both Felten's and Eloundou's indices. The most AI-exposed occupations include software and database professionals, numerical clerks (accounting, audit and ledger clerks), mathematicians and actuaries, business and finance professionals, and associate professionals. These occupations fall among the top 10 most AI-exposed on both the Felten (2021) and the Eloundou (2024) indices. Four of these occupations fall in the high-skill category while the last one includes medium-skill jobs.

Figure 12: Most and least exposed occupations



Notes: *The figure shows the most and least AI exposed 3-digit occupations based on both Felten's and Eloundou's indices. It represents the nonfarm wage employed workers and the skill classification is based on years of formal education.*
Source: *Periodic Labour Force Survey (2018-19 to 2025); Felten et al (2021); Eloundou et. al (2024).*

The least AI-exposed occupations include mining and construction labourers, cleaners and food preparation assistants, welders and moulders, building finishers, and building frame workers and plant operators in mining. Only one of these is a medium-skill occupation while all others are low-skill. In line with the evidence on job polarization, this further reinforces that modern AI tools have the potential to undertake routine, cognitive tasks efficiently. This can further contribute to the hollowing out of medium-skill workers and also displace high-skill workers who perform relatively fewer cognitive tasks in their occupations. While medium-skill workers might get displaced into low-skill occupations, meeting the aspirations of educated workers displaced from high-skill occupations will be a challenge.

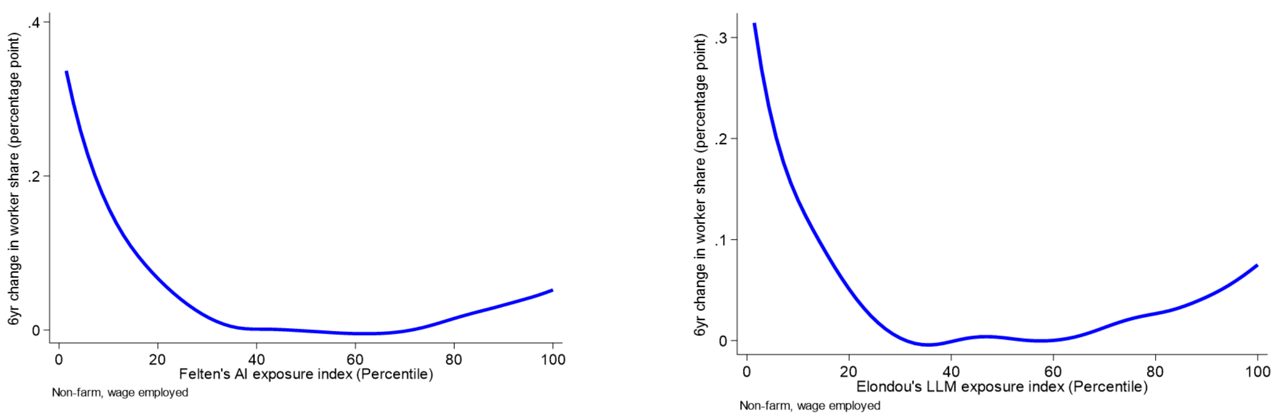
Next, we examine how employment changes are related to AI exposure. We do not use Anthropic's measure of observed adoption since that captures data from 2026, beyond the period of analysis covered in this report.

Employment growth and AI exposure

To assess employment changes in relation to occupational exposure to AI, we plot 7-year changes in worker shares for each occupation (at the 3-digit NCO-2015 level) against the occupation-specific AI exposure indices in Figure 13. Between 2018 and 2025, employment among the least AI-exposed occupations increased the most, though there is noticeable growth among the occupations which are highly exposed to AI as well. The share of workers employed in the least AI-exposed occupations (the bottom 20% occupations in terms of AI-exposure), increased substantially by 1.6 and 1.2 percentage points as per Felten's and Eloundou's exposure indices, respectively, while the most AI-exposed occupations (top 20% occupations in terms of AI-exposure) also grew by 0.6 percentage points during this period as per both Felten's and Eloundou's exposure indices, respectively. Thus, the worker shares in most AI-exposed occupations increased only modestly in comparison to the least-exposed occupations. The U-shaped curve in Figure 13 depicts a more pronounced spike on the left, reflecting this lopsided growth at the lower end of the skill spectrum. Overall, out of the total non-farm wage employed increase of 3.3 p.p. almost half comes from least AI exposed occupations.

Overall, we find that jobs least exposed to AI – such as mining and construction labour, cleaning, and food preparation – have grown the fastest on average, while highly exposed roles in software, finance, and sales have also seen some expansion, though by much less. In contrast, occupations with moderate AI-exposure (between 40-80 percentile) have seen little to no change in workforce shares.

Figure 13: AI exposure and 7-year employment growth



Notes: *The figure plots AI exposure and employment growth at the occupation level for the nonfarm sector wage-employed workers (which includes both salaried and casual workers). The x-axis plots the percentile of occupation-specific AI exposure of 70 3-digit occupations for the two different indices and the y-axis plots the change in worker shares between 2018 and 2025. The smoothed line applies Locally Weighted Scatterplot Smoothing (LOWESS), a non-parametric method that reduces localized data noise and highlights the underlying trend.*
Source: *Periodic Labour Force Survey (2018-19 to 2025); Felten et al (2021); Eloundou et. al (2024).*

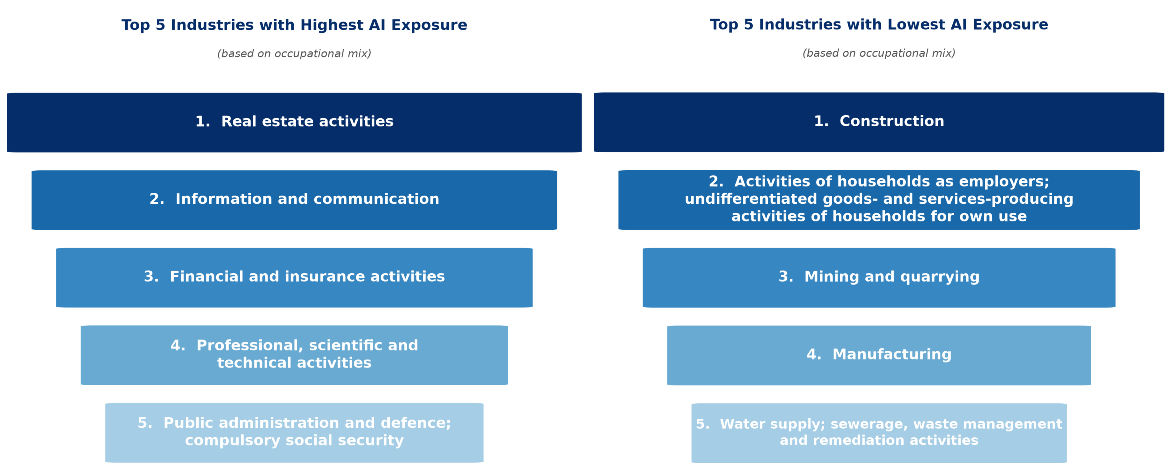
Are some demographic and industry groups more exposed to AI?

We also find evidence for differential AI-exposure by demographic attributes like age and gender of workers. Overall, the average weighted AI exposure score (weighted by the number of workers employed in each occupation) is higher for women than for men. The absolute value of the average AI exposure score for women is 35% higher than that for men based on the Felten index and 15% higher based on the Eloundou index. Thus, on average, female workers tend to be more exposed to AI developments than men.

With regard to age, we find that younger individuals (24 to 35 years of age) are slightly more exposed to AI since they are more likely to be employed in AI-exposed occupations. Younger workers tend to have a higher AI exposure score than the working age population as a whole. On the Felten index, youngsters are 8.5% more exposed than the working age population and on the Eloundou index, they are 4.8% more exposed.

Aggregating occupational AI-exposure to the industry level, we find that AI exposure is more prominent in the knowledge economy and service-led sectors (Figure 14). The aggregation at industry level is done by taking a weighted average of occupational AI exposure scores for each occupation represented in an industry. This allows us to account for the proportion of each occupation within that industry. The industries most exposed to AI include real estate, finance and insurance, information and communication, and professional and scientific activities. On the other hand, industries that exhibit very low vulnerability to AI tend to employ low-skill labour, such as construction, mining, manufacturing, water supply and waste management, and services delivered within households.

Figure 14: Industries exposed to AI

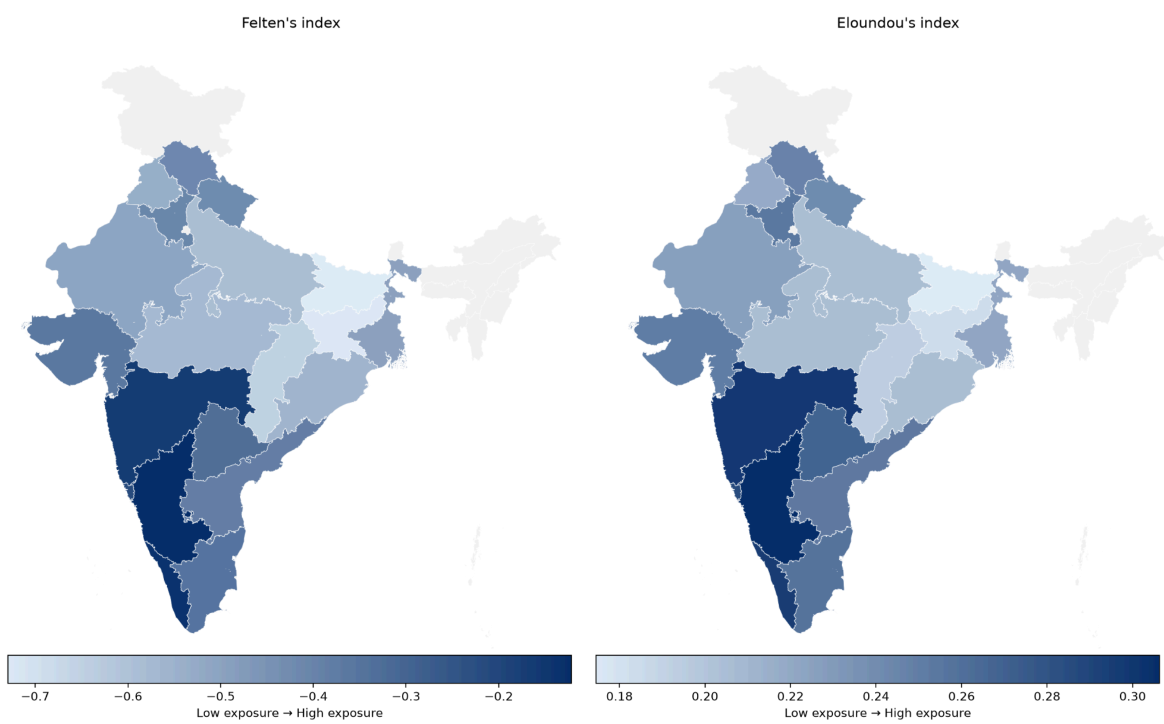


Notes: *This figure shows the most and least exposed industries based on both Felten's and Eloundou's indices in the nonfarm sector. Industry-level exposure is calculated by taking a weighted average of exposure scores using occupational proportions within each industry.*

Source: *Periodic Labour Force Survey (2018-19 to 2025); Felten et al (2021); Eloundou et. al (2024).*

We also aggregate occupational AI exposure for each state of India, by taking weighted averages of occupation-level AI indices weighted by the occupational mix of each state. We find that relatively high-output powerhouses like Maharashtra, Karnataka, Telangana, Goa and Kerala tend to be more exposed to AI due to the concentration of more AI exposed occupations in these states. Bihar, Jharkhand, Chhattisgarh, and Uttar Pradesh are among the states with the lowest AI exposure (Figure 15). These results suggest that any losses or gains from AI are likely to be uneven across demographic groups and regions in the country.

Figure 15: States' AI exposure



Notes: *This figure shows India's AI exposure by state based on both Felten's and Eloundou's indices in the nonfarm sector. State-level exposure is calculated by taking a weighted average of exposure scores using occupational proportions within each state. Shapefile taken from Survey of India.*
Source: *Periodic Labour Force Survey (2018-19 to 2025); Felten et al (2021); Eloundou et. al (2024).*

Box 5: Boosting data infrastructure through a task content survey

Given the rapid pace of AI development, we urgently need to understand how occupations and job roles will evolve in the Indian labour market. This report highlights some of our findings about the impact of AI on the Indian labor market but an important limitation is that current AI-exposure indices are US-based and thus, have limited applicability for the Indian context. Moreover, these indices are likely already outdated since they are not able to capture the usage of evolving AI tools.

In order to understand the impact of AI on labour markets, we need to understand the nature of tasks within each occupation. Occupations are bundles of tasks. AI affects how specific tasks are performed by increasing the speed, efficiency, or accuracy of doing tasks. However, we do not yet understand which tasks are prone to automation and which ones are made more productive by AI in the Indian context.

A crucial missing piece in India's existing data infrastructure is that we do not have granular data on the task content of jobs and especially on the relative importance of tasks that make up a job. Existing AI indices use task data from the Occupational Information Network (O*NET). However, the task content of jobs is substantially different between the USA and other countries (Caunedo et al., 2023; Lewandowski et al. 2022). To understand the impact of AI on the Indian labour market, such task content data is essential.Conducting a survey of workers employed across various occupations in India to collect data on task content and AI usage would be a highly valuable addition to the existing data infrastructure. Such a survey can help answer crucial policy questions about occupational employment trends and skill demand in the future. This data will also inform policies aimed at boosting AI adaptability of the Indian workforce.

LOOKING FORWARD: AREAS OF FOCUS

India's employment challenge is not only to create more work, but to create better work: productive, well-remunerated, and resilient to technological change. The evidence in this report points to three policy priorities.

1. Accelerate the transition to productive nonfarm employment

The persistence of agricultural self-employment and the relatively slow growth of manufacturing and construction jobs suggest that structural transformation remains incomplete. Policy attention must be focused on creating high-productivity jobs. To this end, expanding labour-intensive nonfarm sectors that can absorb workers at scale can be particularly beneficial, especially manufacturing, construction, trade and repair, information and communication, logistics, health services, hospitality, and education. Several of these sectors — such as domestic services, water supply and waste management, construction and manufacturing — also tend to be less exposed to AI-tools, boosting their potential for steady and robust employment growth in the future as well. Given India's low female workforce participation, this transition also needs to be gender-sensitive: public safety, transport, and childcare are crucial for enabling women to move from low-paid or unpaid family work into paid and productive nonfarm employment.

2. Rebuild the occupational middle and raise productivity in low-skill work

We find evidence of job polarization in the last seven years: employment is growing at the lower and upper ends of the skill distribution, while medium-skill occupations show weaker growth. This creates a serious risk for educated youth, especially those completing secondary or post-secondary education, without access to high-quality jobs. If medium-skill opportunities do not expand, many workers may be pushed into low-skill work despite rising educational attainment. Policy should therefore focus on strengthening the occupational middle through industry-linked training, and targeted support for occupations such as technicians, installers, repairers, supervisors, nursing associates, clerical workers, and production-support roles. At the same time, since much of employment growth is occurring in low-skill work, the policy question is not only how to move workers out of such jobs, but how to raise productivity within them. This requires formal contracting, moving the quality of skills upwards, access to credit for micro-enterprises, and productivity-enhancing infrastructure investments.

3. Build AI adaptability into skilling and labour-market planning

AI is likely to affect occupations unevenly. The most exposed occupations are high-skill jobs and routine-cognitive roles. India's skilling system should therefore move towards occupation-specific AI adaptability. Workers in software, finance, clerical, analytical, customer-interface, and technical-assistance roles need training that helps them use AI to complement occupation-specific tasks. Helping workers learn how to use AI tools for their specific industry and occupation will allow for acquisition of transferable skills. At the same time, India lacks systematic task-occupation-skill data that can show what workers actually do within occupations and how these tasks are changing with technology; building such a data architecture is essential for designing responsive skilling policy (See Box 5). Skilling policy should be demand-oriented and curricula should be tied to occupations where wage work is growing. Potential high-growth sectors like health and education may need dedicated policy support.

ENDNOTES

1. International Labour Organization (2024), India Employment Report.
2. The initial PLFS rounds were based on a July to June cycle but, starting from PLFS 2025, key changes to the sampling and data collection procedures were introduced. As a result, the 2025 survey covers the period January to December 2025.
3. One of the challenges in analyzing data from the PLFS is that the weights in the PLFS microdata do not sum up to the national population. In order to obtain numbers that represent the true population, we use census population projections along with proportions from the PLFS data. For example, to calculate the number of workers in the working age population, we estimate the proportion of workers between the ages of 15 to 59 (inclusive) using the PLFS weights. Census population projections (total population) for each year are taken from the Report of the Technical Group on Population Projections, November 2019 (MoHFW). The calculated proportion of the working age population is then applied, separately for each year, onto the population projection to obtain the total estimated number of workers in the working age population. The labour market indicators assessed in this report, including worker shares, number of workers employed in different occupations, sectors, or skill types etc. are all based on such calculations.
4. National Council of Applied Economic Research (2025), India's Employment Prospects: Pathways to Jobs.
5. McMillan, S., Margaret and Dani Rodrik (2011), 'Globalization, Productivity Growth, and Structural Change', Working Paper No. 17143, National Bureau of Economic Research.
6. Amirapu, Amrit and Arvind Subramanian (2015), 'Manufacturing or Services? An Indian Illustration of a Development Dilemma', Working Paper No. 409, Centre for Global Development.
7. Hasan, Rana and Rhea Molato (2019), 'Wages Over the Course of Structural Transformation: Evidence from India', Asian Development Review, MIT Press, vol. 36(2), pages 131-158, September.
8. Hasan, Rana, Sneha Lamba, and Abhijit Sen Gupta (2013), 'Growth, Structural Change, and Poverty Reduction: Evidence from India', South Asia Working Paper Series, Asian Development Bank.
9. Gulati, Nalini, Kanika Mahajan, and Anisha Sharma (2025), 'India at Work: Challenges and the Road Ahead', Policy Discussion Paper, Isaac Centre for Public Policy, Ashoka University, 17 July.
10. Ashwini Deshpande (2025), "Too good to be true? Steadily rising female labour force participation rates in India" Centre for Economic Data and Analysis (CEDA), Ashoka University.
11. In public interest, this concordance is made available publicly and can be accessed with this GitHub repository
12. Ministry of Labour and Employment (2015), National Classification of Occupations 2015 (Code Structure) Vol 1, Government of India
13. Lewandowski, Piotr, Albert Park, Wojciech Hardy, Yang Du, and Saier Wu (2022), 'Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data', The World Bank Economic Review, Volume 36, Issue 3 (pp 687–708).
14. The skill classification of the sixth division is also contentious. While the official International Labour Organization (ILO) skill-level classification classifies this under medium-skill, in developing countries this typically reflects low-skill labour having one of the lowest wages. Overall, the agricultural sector in India has negligible high skill workers and almost all lie in the sixth division. (See: Khurana, Saloni, and Kanika Mahajan (2023) and "Tasks, Skills, and Institutions: The Changing Nature of Work and Inequality" edited by Carlos Gradín, Piotr Lewandowski, Simone Schotte, and Kunal Sen, Oxford University Press)
15. The NCO-2004 was the precursor to NCO-2015. The initial waves of the PLFS identified occupations using NCO-2004 while the recent PLFS rounds employ the latest NCO-2015 classification. The concordance between NCO-2004 and NCO-2015 was available at the 6-digit occupation level only. Therefore, we created a concordance between NCO-2004 and NCO-2015 at the 3-digit code level which is used to analyze PLFS rounds together over time in this report. In public interest, this concordance is made available publicly and can be accessed with this GitHub repository.

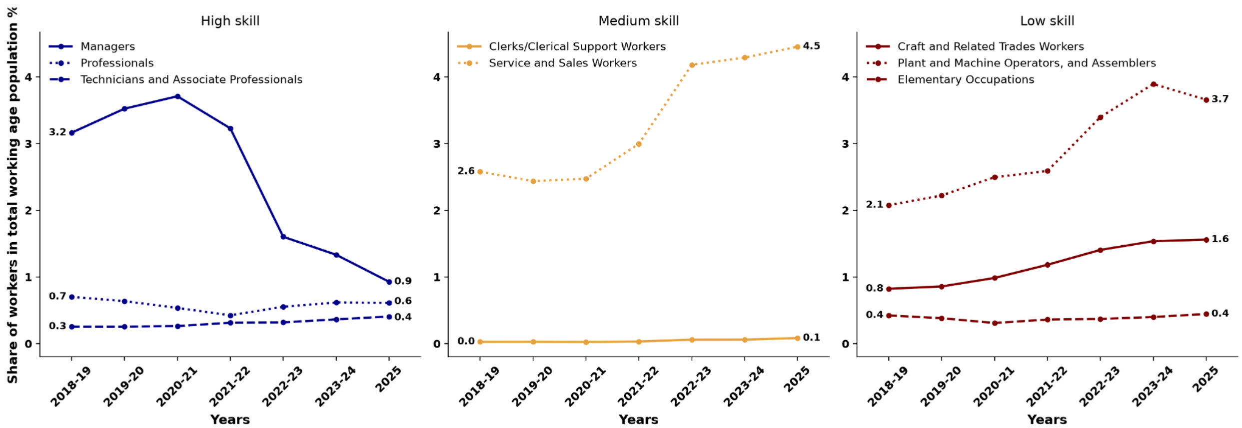
16. For the purposes of presentation, all the graphs for the nonfarm sectors using the NCO-based skill classification do not feature the 1-digit NCO category of "Skilled Agricultural, Forestry and Fishery Workers" (NCO division 6). This is because their share in the nonfarm sector is only 0.1 percent out of the entire working age population. Workers in this division comprise cultivators (fruits, grains, and vegetables), gardeners, horticulture and nursery growers, livestock and dairy producers, apiarists, hunters and trappers, aquaculture workers, deep sea fishery workers, etc. These workers are employed in various industries in the nonfarm sectors, including manufacturing (beverages, food products, textiles, tobacco, wearing apparel, and wood products), retail and wholesale trade, personal services, and services related to buildings and landscaping activities, and are classified as medium-skilled workers based on the NCO skill classification. While this category has been removed from the graphs representing the nonfarm Indian economy, they are included in the analytical sample.
17. Nominal daily wages are deflated using the Consumer Price Index (CPI) series, from the Ministry of Statistics and Programme Implementation (MoSPI), separately for rural and urban sectors. For the PLFS years 2018 to 2024, the annual CPI is calculated as a simple average of the monthly indices between June and July whereas for 2025, the annual CPI is an average of the monthly indices from January to December. All the annual indexes are rebased to 2017 for comparability. Furthermore, the nominal daily wage is winsorized at the 99.5th percentile before applying the deflators.
18. A caveat here is that wage growth, especially below the median wage, can also be affected by institutional factors such as increases in sector-specific minimum wages.
19. A handful of occupations change skill levels when we compare these two systems for measuring skills. For example, Supervisors and Technicians across mining, manufacturing and construction industries are classified as medium-skill based on years of education but they are classified as high-skill by the NCO-2015. The same switch occurs with Nursing and Midwifery Associate Professionals. On the other hand, Installers and Repairers are classified as medium-skill based on education levels, but low-skill according to the NCO-2015. However, the topmost 5 growing occupations remain consistent regardless of which system for measuring skills is used. Additionally, the only new occupation that gets added is Client Information Workers in the place of Secondary Education Teachers when we switch to the NCO based skill classification.
20. Following the 'routinization' framework (see Autor et al., 2003), tasks are divided into routine and non-routine categories. Routine (or codifiable) tasks are procedural, rule-based activities understood to be fully specified as a series of programmed instructions that can be executed by a machine; these are further subdivided into routine cognitive tasks (e.g., bookkeeping and clerical support) and routine manual tasks (e.g., repetitive assembly). Conversely, non-routine tasks cannot be easily codified and are split into abstract (non-routine cognitive) tasks requiring problem-solving, intuition, and creativity (characteristic of professional, managerial, and technical occupations) and non-routine manual tasks requiring situational adaptability, physical flexibility, and in-person interaction (characteristic of service and maintenance roles).
21. Acemoglu, Daron and David Autor (2011), 'Skills, Tasks, and Technologies: Implications for Employment and Earnings', Working Paper No. 16082, National Bureau of Economic Research.
22. Goos, Marten, Alan Manning, and Anna Salomons (2009), 'Job Polarization in Europe', American Economic Review, Vol. 99, no. 2, May 2009 (pp. 58–63).
23. Khurana, Saloni and Kanika Mahajan (2020), 'Evolution of wage inequality in India (1983-2017): The role of occupational task content', Working Paper No 2020/167, UNU WIDER
24. Felten, Edward, Manav Raj, and Robert Seamans (2021), 'Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses', Strategic Management Journal, Volume 42, Issue 12 (pp. 2195-2217).
25. Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock (2024), 'GPTs are GPTs: Labor market impact potential of LLMs', Science, Volume 385, Issue 6702 (pp. 1306-1308).
26. Massenkoff, Maxim and Peter McRory (2026), 'Labour Market Impacts of AI: A new measure and early evidence', Anthropic. Unlike older theoretical exposure scores (which ask if AI could do this job in the future) Anthropic's observed exposure metric is empirical. It measures how people are actually using AI

today. Anthropic calculates this by taking a random sample of millions of real, anonymized conversations from Claude (both the consumer app and the developer API) between February 5th 2026 - February 12th 2026, and using an AI system to map those conversations to the ~18,000 specific job tasks defined by the U.S. Department of Labor's O*NET database.

27. The International Labour Organization (ILO) has developed a system to classify all occupations in the world, based on the tasks they comprise, which is called the International Standard Classification of Occupations (ISCO). Similarly, the US has their own system called the Standard Occupational Classification (SOC) and the classification system in India is called the National Classification of Occupations (NCO) which uses ISCO as its foundation. Because existing AI indices in the literature map to US occupations under the SOC, a multi-step crosswalk is required to harmonize these exposure scores with the Indian NCO system used in the PLFS. We build this concordance in several steps. First, the BLS crosswalk between US SOC 2010 and ISCO-08 is merged with the ILO's crosswalk between ISCO-08 and ISCO-88 because these are key inputs in enabling a merging of occupational classifications between countries. Because the 4-digit ISCO-88 codes can be harmonized to the 3-digit aggregation in India's NCO 2004, we establish this link and subsequently merge in a custom concordance—developed by the authors—between NCO 2004 and the updated NCO 2015. Lastly, a BLS crosswalk between SOC 2018 and SOC 2010 is integrated to bridge newer indices. As a result, we obtained a master crosswalk linking SOC 2010 and SOC 2018 to NCO 2015. We then map the specific AI indices. Felten's AI exposure index (available at the 6-digit SOC 2010 level) is mapped directly to NCO 2015 using this crosswalk. For Eloundou's LLM exposure index (available at the 8-digit O*NET/SOC 2018 level), the codes are first truncated to their 6-digit equivalents, mapped backward to SOC 2010, and then bridged to NCO 2015. In the final step, the AI scores for both indices are averaged, using a simple average, at the 3-digit NCO level to facilitate merging with the PLFS dataset.
28. Michael Webb (2020), '[The Impact of Artificial Intelligence on the Labor Market]', Stanford University.
29. Chopra et al. (2025), '[The Iceberg Index: Measuring Workforce Exposure in the AI Economy]', MIT.

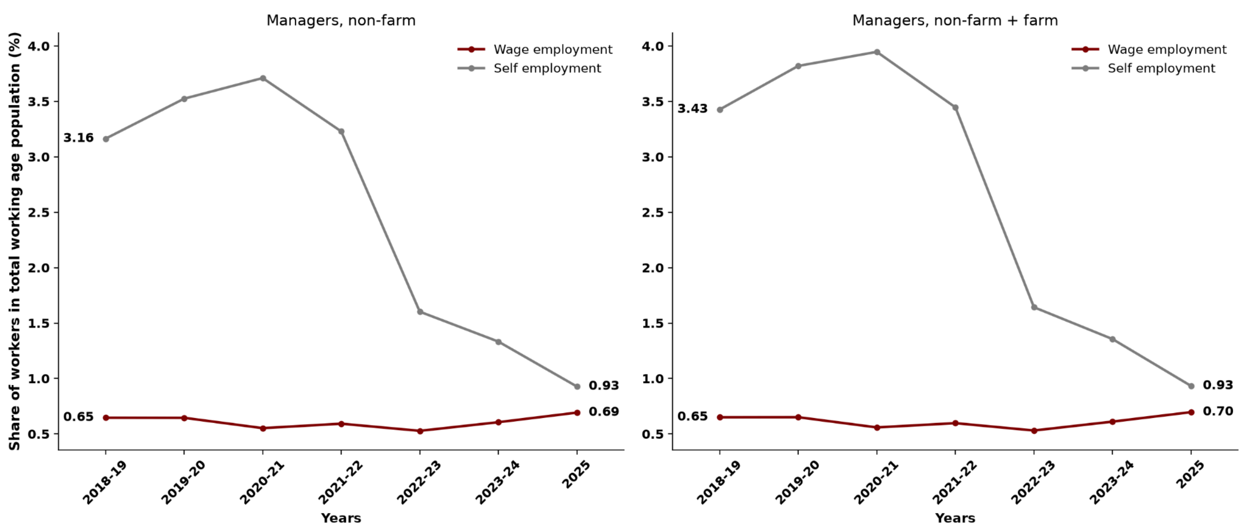
APPENDIX

Figure A1: Worker shares of self-employed workers in the nonfarm sector



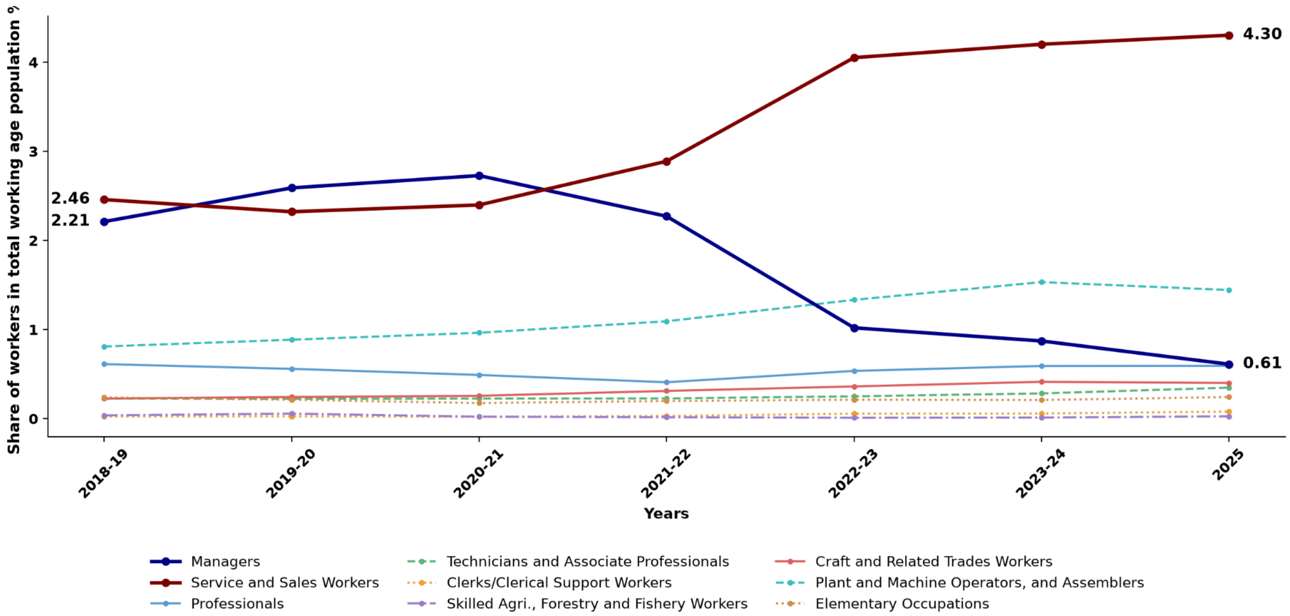
Notes: *The figure plots workforce participation rates across 1-digit occupation divisions for nonfarm self-employed workers. Skill is defined as per the NCO classification. Employment is as per the current weekly status (age 15-59).*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Figure A2: Worker shares for self-employed Managers have declined sharply



Notes: *The figure shows workforce participation rate for Managers (NCO division 1) split into wage and self-employed workers. Wage-employed includes both salaried and casual workers. Employment is as per the current weekly status (age 15-59).*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Figure A3: Possible reclassification of self-employed Managers in the service sector



***Notes**: The figure plots workforce participation rates for self-employed workers in the service sector. Employment is as per the current weekly status (age 15-59).*
***Source**: Periodic Labour Force Survey (2018-19 to 2025).*

Figure A4: Employment growth in nonfarm employment

Figure A4(a): Wage-employed workers

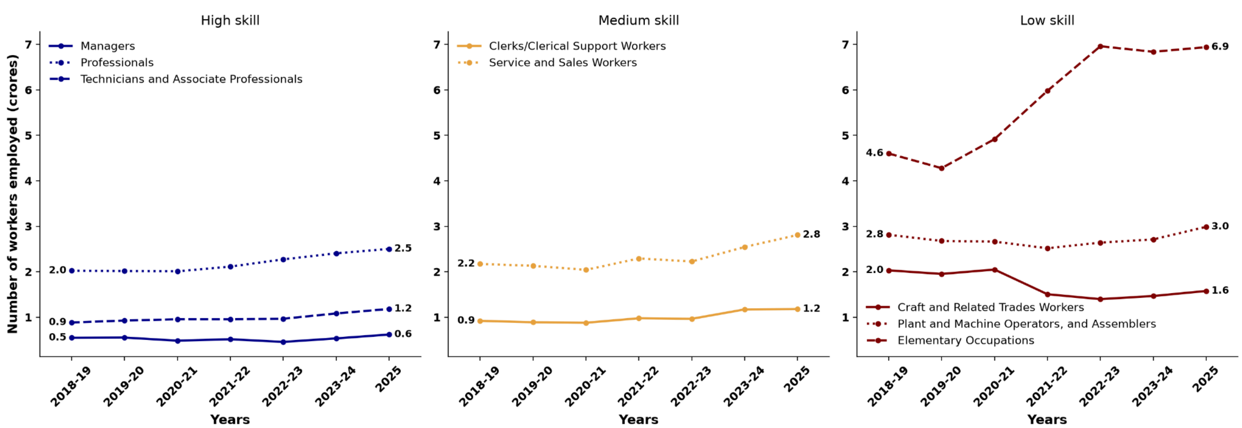
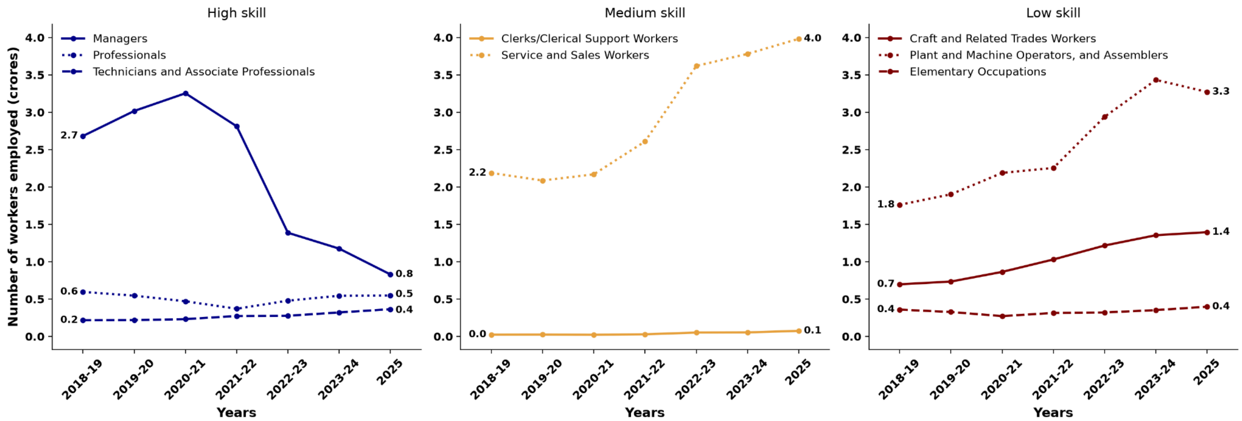
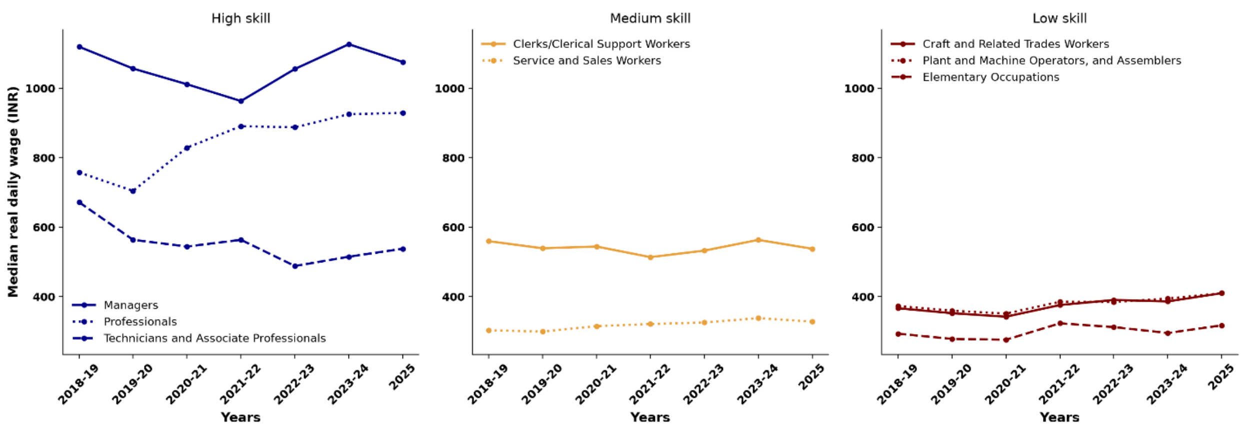


Figure A4(b): Self-employment workers



Notes: *The figure shows the trend in the number of employed workers in the nonfarm sector split into wage- and self-employed workers. Skill is defined as per the NCO classification. Wage-employed includes both salaried and casual workers. Employment is as per the current weekly status (age 15-59).*
Source*: Periodic Labour Force Survey (2018-19 to 2025). Census population projections are used to estimate absolute numbers from survey calculations.*

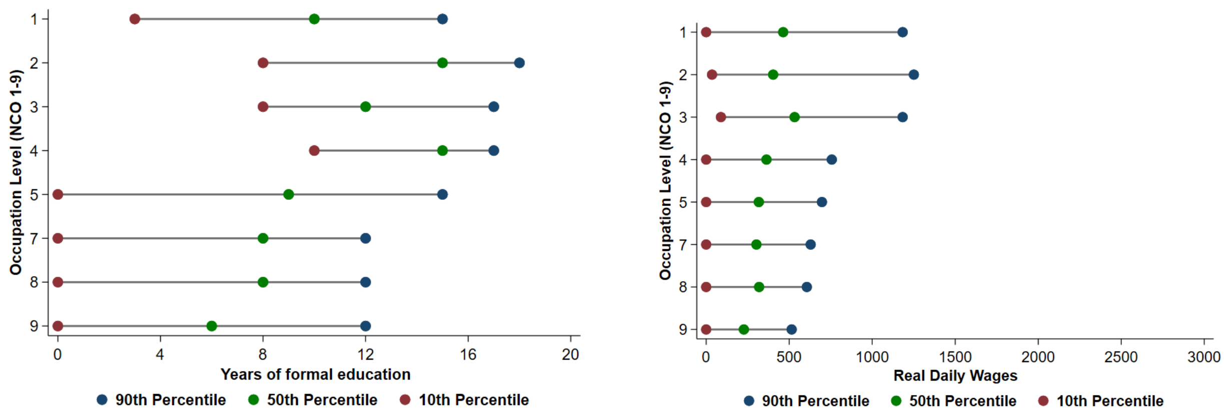
Figure A5: Real wages for wage-employed workers in the nonfarm sector



Notes*: The figure plots the trend in the median real daily wage for the nonfarm sector wage-employed workers (which includes both salaried and casual workers). Skill is defined as per the NCO classification. Daily wages are based on the daily status (age 15-59). The unit is ₹.*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

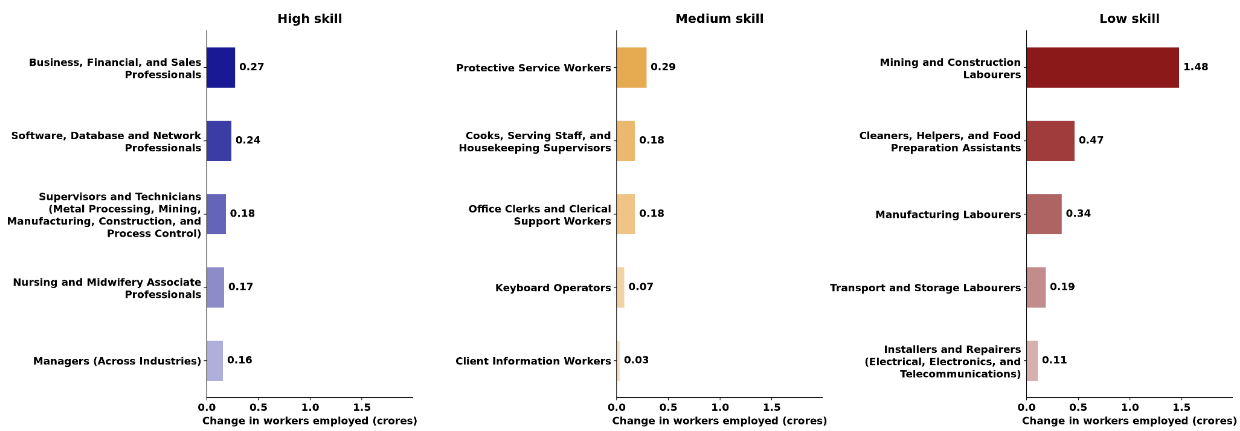
Figure A6: Distribution of years of formal education and real daily wages for self-employed

workers in the nonfarm sectors



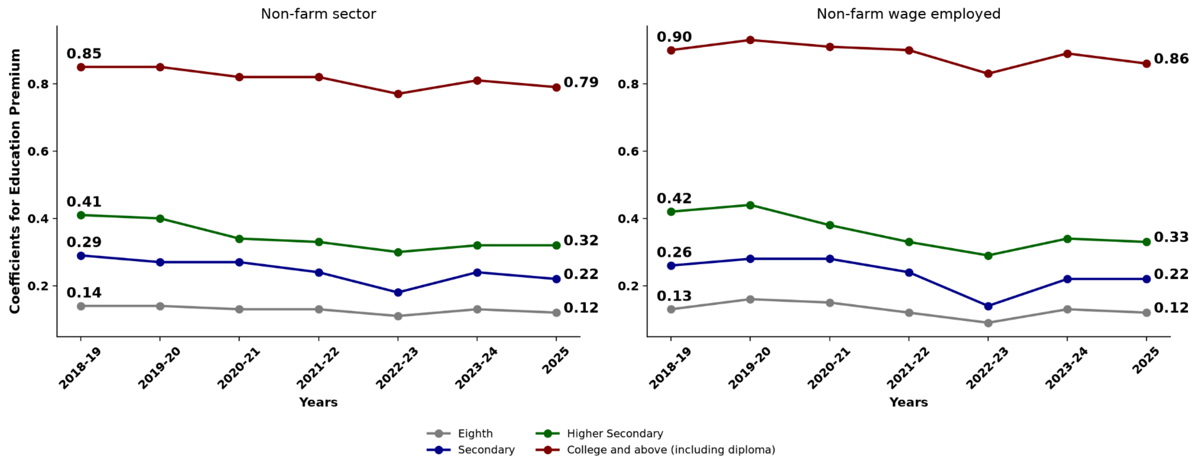
Notes: *The chart plots a range from the 10th to the 90th percentile of years of education and real daily wages for each of the 9 broad occupational divisions in the NCO representing the nonfarm self-employed workers. Daily wages are based on the daily status (age 15-59). Category 6 is excluded from the graph since it largely comprises agricultural occupations. The unit is ₹.*
Source: *Periodic Labour Force Survey (2018-19 to 2025).*

Figure A7: Fastest growing occupations for NCO-based skill classification



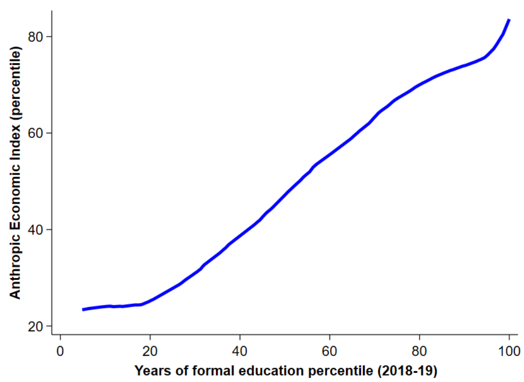
Notes*:This figure shows the fastest growing 3-digit occupations (in terms of workers added) in the nonfarm sector among wage-employed workers (which includes both salaried and casual workers). Skill definition is based on the NCO classification. Change is in crores.*
Source*: Periodic Labour Force Survey (2018-19 to 2025). Census population projections are used to estimate absolute numbers based on survey calculations.*

Figure A8: Changes in returns to education in India over time



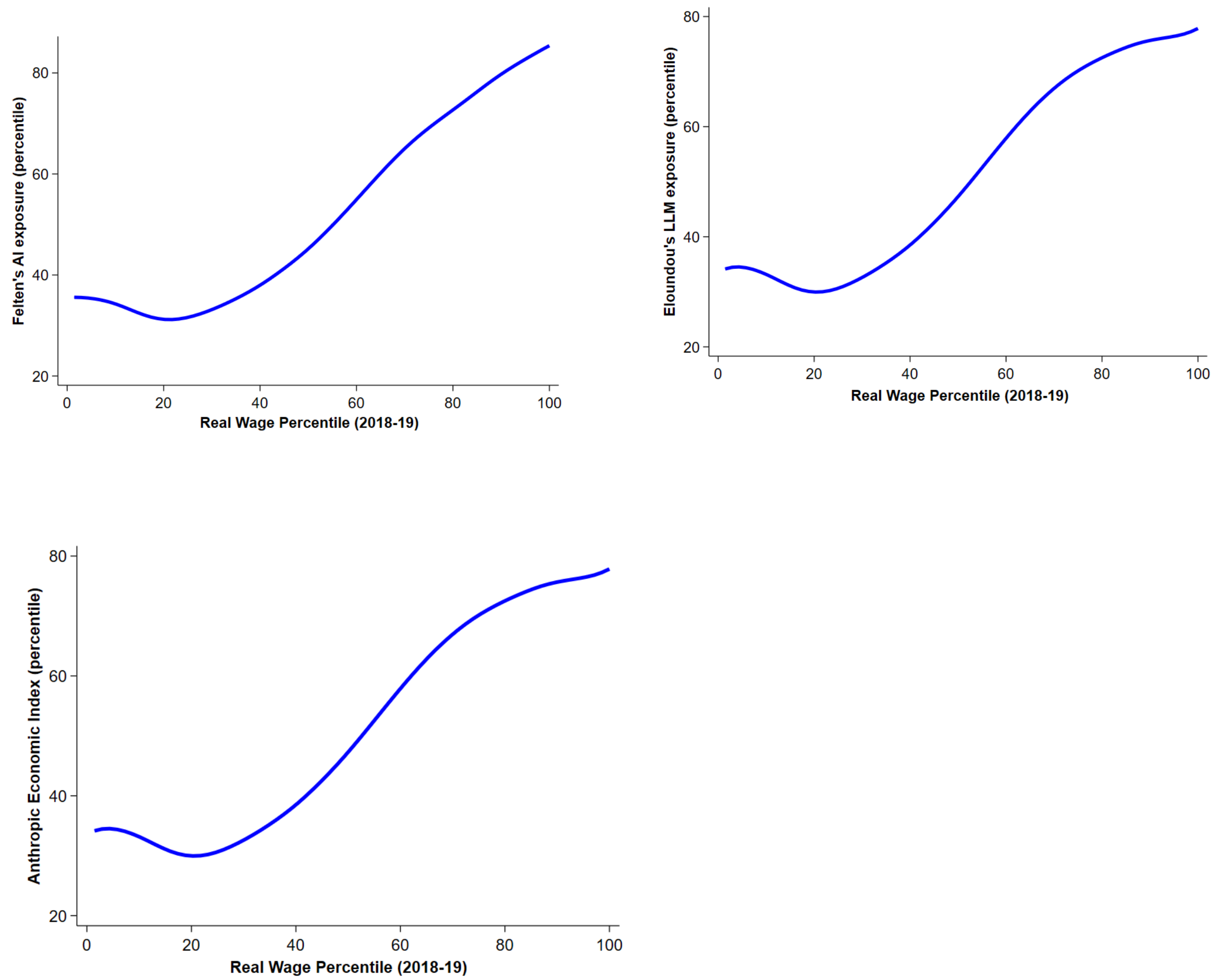
Notes: *The graph plots regression coefficients for education wage premiums for different levels of education over the span of 7 years separately for the nonfarm sector as a whole and the nonfarm wage-employed. The coefficients represent the wage premium for each level of education relative to the reference category of workers who have not completed eighth class, including those who are illiterate. The regression includes controls for a quadratic function for age, gender, and industrial sector.*
Source*: Periodic Labour Force Survey (2018-19 to 2025)*

Figure A9: AI exposure and skills based on years of education for Anthropic Economic Index



Notes*: The figure plots AI exposure across the skill distribution (measured by years of formal education) for the nonfarm wage employed workers.The x-axis plots the percentile of years of formal education and the y-axis plots occupation-specific AI exposure for the Anthropic Economic Index. The smoothed line applies Locally Weighted Scatterplot Smoothing (LOWESS), a non-parametric method that reduces localized data noise and highlights the underlying trend.*
Source: *Periodic Labour Force Survey (2018-19 to 2025); Anthropic Economic Index (2026)*

Figure A10: AI exposure and skills based on real wage



Notes: *The figure shows AI exposure across skill distribution (measured in real wages) for nonfarm wage-employed workers (which includes both salaried and casual workers). The x-axis plots the percentile of real wages and the y-axis plots occupation-specific AI exposure for the three different indices. The smoothed line applies Locally Weighted Scatterplot Smoothing (LOWESS), a non-parametric method that reduces localized data noise and highlights the underlying trend.*
Source: *Periodic Labour Force Survey (2018-19 to 2025); Felten et al (2021); Eloundou et. al (2024); Anthropic Economic Index (2026)*

Table A1: Occupational families under the top-5 fastest growing 3-digit occupations in Figure 8 and Figure A7

Low Skill	
931	**Mining and Construction Labourers**

9311	Mining and Quarrying Labourers
9312	Civil Engineering Labourers
9313	Building Construction Labourers
9_n	**Cleaners, Helpers, and Food Preparation Assistants**
9111	Domestic Cleaners and Helpers
9112	Cleaners and Helpers in Offices, Hotels and Other Establishments
9121	Hand Launderers and Pressers
9122	Vehicle Cleaners
9123	Window Cleaners
9411	Fast Food Preparers
9412	Kitchen Helpers
932	**Manufacturing Labourers**
9321	Hand Packers
9329	Manufacturing Labourers Not Elsewhere Classified
933	Transport and Storage Labourers
9331	Hand and Pedal Vehicle Drivers
9332	Drivers of Animal-Drawn Vehicles and Machinery
9333	Freight Handlers
9334	Shelf Fillers
5_n1	**Cooks, Serving Staff, and Housekeeping Supervisors**
5120	Cooks
5131	Waiters
5132	Bartenders
5151	Cleaning and Housekeeping Supervisors in Offices, Hotels and Other Establishments
5152	Domestic Housekeepers
5153	Building Caretakers

Medium Skill	
541	Protective Service Workers
5411	Fire Fighters
5412	Police Officers
5413	Prison Guards
5414	Security Guards
5419	Protective Services Workers Not Elsewhere Classified
3_n7	Supervisors and Technicians (Metal Processing, Mining, Manufacturing, Construction, and Process Control)
3121	Mining Supervisors
3122	Manufacturing Supervisors
3123	Construction Supervisors
3131	Power Production Plant Operators
3132	Incinerator and Water Treatment Plant Operators

3133	Chemical Processing Plant Controllers
3134	Petroleum and Natural Gas Refining Plant Operators
3135	Metal Production Process Controllers
3139	Process Control Technicians Not Elsewhere Classified
4_n1	Office Clerks and Clerical Support Workers
4110	General Office Clerks
4411	Library Clerks
4412	Mail Carriers and Sorting Clerks
4413	Coding, Proofreading and Related Clerks
4414	Scribes and Related Clerks
4415	Filing and Copying Clerks
4416	Personnel Clerks
4419	Clerical Support Workers Not Elsewhere Classified
322	Nursing and Midwifery Associate Professionals
3221	Nursing Associate Professionals
3222	Midwifery Associate Professionals
7_n1	Installers and Repairers (Electrical, Electronics, and Telecommunications)
7411	Building and Related Electricians
7412	Electrical Mechanics and Fitters
7413	Electrical Line Installers and Repairers
7419	Electrical and Electronic Equipment Mechanics and Fitters and Related Workers Not Elsewhere Classified
7421	Electronic Mechanics and Servicers
7422	Information and Communications Technology Installers and Servicers
422	Client Information Workers
4221	Travel Consultants and Clerks
4222	Contact Centre Information Clerks
4223	Telephone Switchboard Operators
4224	Hotel Receptionists
4225	Inquiry Clerks
4226	Receptionist (General)
4227	Survey and Market Research Interviewers
4229	Client Information Worker Not Elsewhere Classified

High Skill	
2_n3	Business, Financial, and Sales Professionals
2411	Accountants
2412	Financial and Investment Advisors
2413	Financial Analysts
2421	Management and Organization Analysts
2422	Policy Administration Professionals
2423	Personal and Careers Professionals
2424	Training and Staff Development Professionals
2431	Advertising and Marketing Professionals

2432	Public Relations Professionals
2433	Technical and Medical Sales Professional (Excluding ICT)
2434	Information and Communications Technology Sales Professionals
2_n1	Software, Database and Network Professionals
2511	System Analysts
2512	Software Developers
2513	Web and Multimedia Developers
2514	Applications Programmers
2519	Software and Application Developers and Analysts Not Elsewhere Classified
2521	Database designers and Administrators
2522	Systems Administrators
2523	Computer Network Professionals
2529	Database and Network Professionals Not Elsewhere Classified
1_n	Managers (Across Industries)
1211	Finance Managers
1212	Human Resource Managers
1213	Policy and Planning Managers
1219	Business Services and Administration Managers Not Elsewhere Classified
1221	Sales and Marketing Managers
1222	Advertising and Public Relation Managers
1223	Research and Development Managers
1311	Agricultural and Forestry Production Managers
1312	Aquaculture and Fisheries Production Managers
1321	Manufacturing Managers
1322	Mining Managers
1323	Construction Managers
1324	Supply, Distribution and Related Managers
1330	Information and Communication Technology Services
1341	Child Care Service Managers
1342	Health Services Managers
1343	Aged Care Services Managers
1344	Social Welfare Managers
1345	Education Managers
1346	Financial and Insurance Service Branch Managers
1349	Professional Services Managers Not Elsewhere Classified
1411	Hotel Managers
1412	Restaurant Managers
1420	Retail and Wholesale Trade Managers
1431	Sports, Recreation and Cultural Centre Managers
1439	Services Manager Not Elsewhere Classified
413	Keyboard Operators
4131	Typists and Word Processing Operators
4132	Data Entry Clerks
233	Secondary Education Teachers
2330	Secondary Education Teachers

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