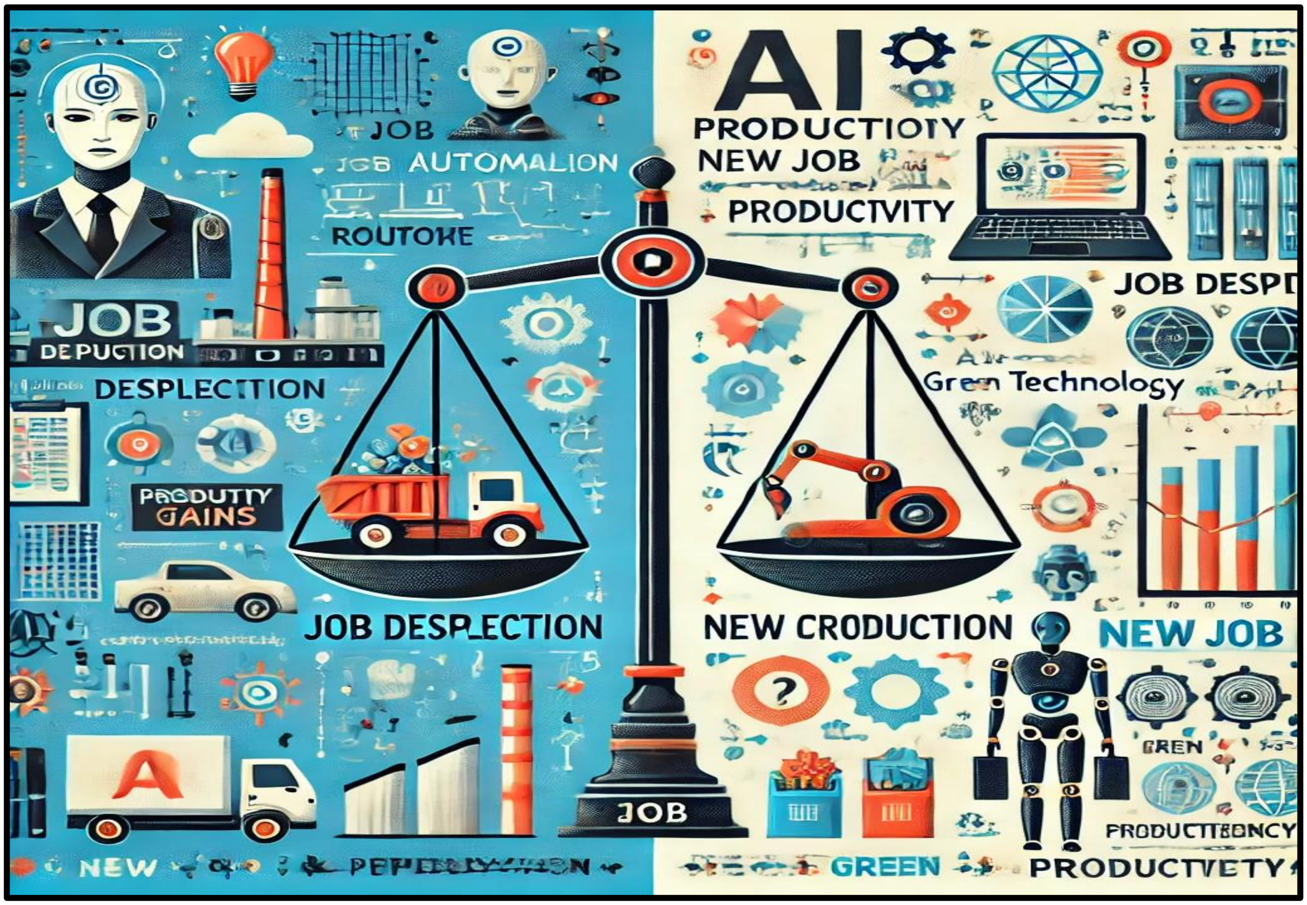

The above picture has been created using AI

Impact of Emerging Technologies on Jobs and Productivity

Katya Ring | Shruti Singh | February 2025

Disclaimer: This paper has been prepared as a part of the UK-India Economic Policy Exchange Programme for Indian Economic Service Officers. The content of this paper is based on research and analysis conducted by the author(s) in an academic or professional capacity and is intended for informational purposes only.The views and opinions expressed in this paper are those of the author(s) and do not reflect the official position or policy of the Government of India.

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Introduction

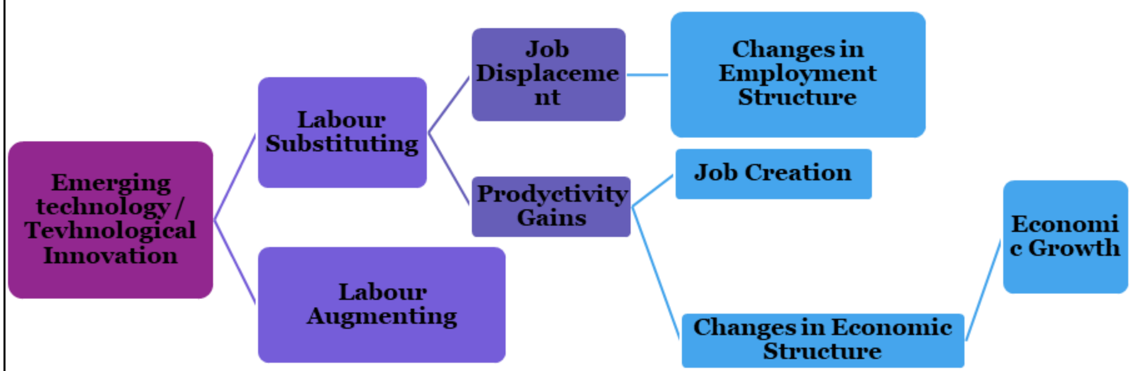
In 1930, the economist John Maynard Keynes, in his essay 'Economic Possibilities for our Grandchildren' warned about the phenomenon of technological unemployment- 'This means unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour'. The question arises whether the current technological upheaval, driven by the advent of AI and automation, will lead economies toward technological unemployment, as predicted by Keynes, or whether it will result in employment creation, enhanced productivity, and the advancement of the economic frontier, accompanied by welfare gains for all.

Technology has transformed economies throughout history, fundamentally altering production possibilities and processes, consumption patterns, as well as rewards for the different kinds of skills that workers bring to the labour market. Modern technologies such as machine learning and robotics are set to continue this trend, perhaps at an unprecedented speed and scale. However, all major technological innovations, starting from the great Industrial Revolution, have also coincided with a fear of technological unemployment and a significant churning in labour markets. The current wave of emerging technological progress is no exception.

New technologies do not simply replace labour with machines; automation often leads to lower prices in a competitive market. Additionally, technology can enhance product quality, customisation, and speed of delivery. All of these improvements can result in increased demand. If demand rises significantly, employment can grow even if the amount of labour needed per output unit decreases. Of course, job losses in one industry may be balanced by job growth in other industries.

This new technology revolution involving AI and automation is expected to create more disruptions in the economy as compared to previous industrial revolutions due to three key factors: speed (changes are occurring at a much faster pace than ever before), breadth and depth (so many radical changes are occurring simultaneously), and the complete upheaval of entire systems (Schwab, 2016). The following box shows how technology can impact the economy based on the literature and economic theory:

Impact of Technological Change on the Economy



How will emerging technologies impact economies? - A literature review

THEORIES OF TECHNOLOGICAL CHANGE

Citing the standard compensation theory, researchers have argued that there are many compensation mechanisms which, in the long run, can counterbalance the initial negative impact of labour saving technological changes (Vivarelli, 2012). For example, technology may reduce the demand for labour in traditional industries; however, it simultaneously increases the demand for labour in new industries that emerge from technological innovations. Similarly, technological progress reduces the unit cost of production and if demand for goods is price elastic, the overall demand goes up, leading to an increase in demand for labour (Smolny, 1998). Yet another mechanism works through an increase in income. Since technological progress increases labour productivity, it can translate into an increase the income of labour and, hence higher consumption. Finally, the compensation mechanism can work through a decrease in real wages.

In a competitive market with perfect substitutability between labour and capital, technological unemployment causes a reduction in wages, which induces firms to use more labour. The compensation theory is not free from limitations as all compensation mechanisms mentioned above are based on one or another assumption that may or may not pass the test of reality. For example, job creation through a reduction in unit cost is possible only in perfectly competitive markets where the reduction in unit cost is passed on to consumers. In the case of oligopoly markets, this mechanism may not work at all as producers may decide to increase their profits rather than passing on the benefits to consumers.

Job creation via an increase in income is possible only if the benefits of increase in productivity are shared with labour, which may or may not be the case in today's globalized world where labour unions have become extremely weak. Similarly, the idea of job creation through reduction in wages not only collides with the Keynesian idea of effective demand, but also depends on the level of labour market flexibility (for detail see Vivarelli, 2012). Nonetheless, despite all these limitations, the theory of compensation mechanism has withstood the test of time as world has not witnessed any increase in structural unemployment despite many waves of technological revolution in the past.

The technology-induced-unemployment or end-of-work hypothesis may be farfetched. However, there is a consensus that technological change always affects labour by changing the job mix and skill demand. The adoption of new technology makes a few traditional skills and jobs redundant while creating the demand for a new set of skills, leading to a labour market disequilibrium which could result in higher wage disparities. It is now widely documented that the ICT revolution has also coincided with an increase in wage disparity across the globe.

Some researchers argue that the recent wave of technological change has been biased towards high-skilled and educated workers. The advocates of **skill biased technological change (SBTC)** cite two facts to prove their point; first, the increase in demand for skilled workers has been driven by within rather than between industries. Second, there has been a very strong within-sector correlation between various indicators of technological change and an increase in demand for skilled workers. The hypothesis of SBTC is not only conceptually attractive, but it has also proved empirically quite successful (Autor and Dron, 2013). However, of late, the SBTC framework has received a lot of criticism for equating education with skill and also for its inability to explain the mechanism by which technology affects the demand for different categories of labour or skill groups. Moreover, strong evidence of labour market polarization in many countries has also raised concerns about the validity of SBTC.

Some researchers have recently tried to address these limitations by proposing a hypothesis of **task-biased technological change** (Goos et al., 2009, Autor and Dron, 2013). Instead of dividing labour into skilled and unskilled categories, these models try to understand the skill requirement of different jobs through a task-based framework. These models categorize the tasks performed by labour into two broad groups, routine tasks and non-routine tasks, both of which are imperfect substitutes of each other. The routine tasks are those which can be codified and therefore can be easily performed by machines. By contrast, non-routine tasks require human interaction and hence cannot be mechanized easily. The non-routine tasks are further divided into two sub-groups; nonroutine abstract tasks, and non-routine manual tasks. These models illustrate that recent improvements in ICT and a consequent decline in the price of ICT capital has reduced the labour input demand for routine tasks. By contrast, it has increased the labour input demand for non-routine tasks in general and non-routine abstract tasks in particular, which are complementary to computerization. Since non-routine tasks intensive occupations are concentrated at the top and bottom of the wage pyramid, it has led to polarization of the labour market. In short, these models suggest that recent spurts in technology have increased the demand for high-skill workers at the cost of intermediate-skill workers.

ESTIMATES OF THE IMPACT OF EMERGING TECHNOLOGIES ON GDP AND PRODUCTIVITY

There is a growing body of literature surrounding the potential impact of emerging technologies on productivity and GDP growth. As the impact of AI is still highly uncertain, these estimates are highly dependent on the assumptions and methodology used, and there is an extensive range of estimates. However, this note will briefly summarise the eminent literature in this space to set out the context and channels through which emerging technologies might impact productivity growth.

AI increases productivity growth and GDP through several channels. Firstly, through the substitution channel, AI can result in the automation of tasks reducing labour costs and increasing time efficiency, increasing productivity. Secondly, AI augments human capabilities, which means workers may have access to better information through the use of technology, whilst AI may automate some part of their job, which can allow workers to increase their time spent on higher productivity tasks. Furthermore, AI increases R&D and innovation and may reallocate resources to higher productivity roles and sectors.

Acemoglu (2024) created a theoretical model to estimate the effect of AI on productivity, specifically on TFP growth. The approach uses a task-based model, estimating the macroeconomic effects as a function of the share of tasks in the economy that are exposed to AI and the average cost savings of the tasks due to AI. It adjusts the share of exposed tasks by those for which it will be economically profitable to use AI, accounting for the fact that whilst it might be possible for technology to complete some tasks, in some instances, it is more cost-effective to use labour. Acemoglu estimates the TFP effects to be 0.7 per cent in aggregate - approximately 0.07 per cent annually.

However, Aghion and Bunel (2024) used Acemoglu's model but updated some of the key assumptions with their own readings of the literature. They suggest a much higher proportion of tasks will be exposed to AI and there will be greater cost savings from these than Acemoglu. They estimate aggregate productivity growth to rise by 0.68 per cent annually - nearly 10x higher than Acemoglu's estimate.

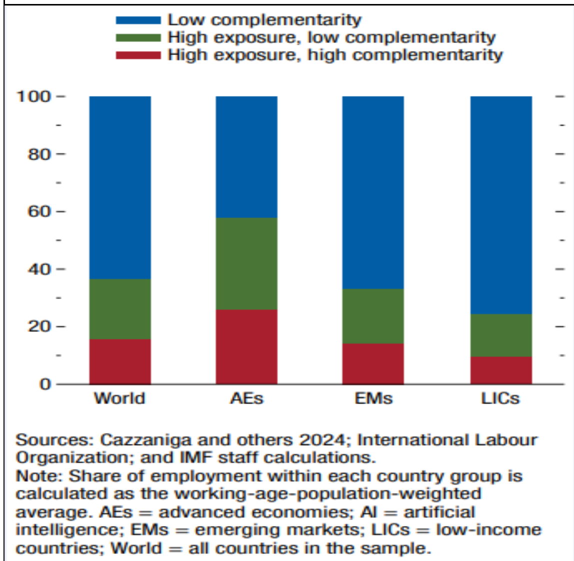
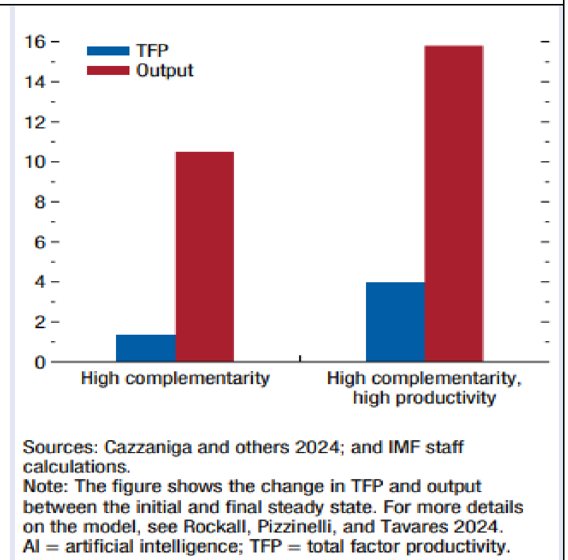
Overall, this demonstrates the uncertainty of forecasting the potential productivity benefits of AI. However, whilst the scale dramatically differs, there is consensus on the direction of the effect, agreeing that AI will have a positive effect on productivity and GDP growth. Therefore, this broadly indicates that firms will have an incentive to adopt AI, and looking purely from a GDP growth perspective, governments may wish to incentivise the adoption of AI.

In the IMF's April 2024 WEO, the IMF assessed the potential impact of AI on productivity. They use a model that combines the potential exposure of the workforce to AI technologies with the potential complementarity – i.e. the potential for augmentation within occupations. The IMF assess on a global level that AI could boost productivity gains by 0.1 to 0.8 per cent annually over a decade. There is a significant disparity in AI exposure between country groups—approximately 60 per cent of jobs in advanced economies are susceptible to changes as a result of AI, compared with 40 per cent in emerging market economies and 26 per cent in low-income countries.

In advanced economies, AI is expected to enhance productivity in half of these exposed jobs, signalling a positive impact. For the other half, AI integration could automate tasks, potentially reducing labour demand and wages and even leading to job obsolescence. In contrast, emerging market and developing economies are less likely to experience immediate disruption but may also see fewer benefits from AI. Many lack the necessary infrastructure and skilled workforce to effectively leverage AI technology, raising concerns that, over time, AI could exacerbate inequality across countries.

However, they assess that in the UK this impact could range from 0.9 to 1.5 per cent a year due to the UK's robust digital infrastructure, skilled labour force, innovation ecosystem and regulatory framework. Meanwhile, they assess that many emerging markets and developing economies lag in preparedness for AI, largely due to a smaller proportion of workers in high-exposure and high-complementarity occupations.

Chart: Employment Shares by AI Exposure and Complementarity	**Chart : Impact of AI on TFP and Output in the United Kingdom**

<table>
<tr><td>(Percent of employment)</td><td></td></tr>
<tr><td>
</td><td>
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<tr><td colspan="2">Source: WEO 2024</td></tr>
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EMERGING TECHNOLOGIES: TRANSFORMING KEY OCCUPATIONS, SECTORS, AND SKILLS

This section will summarise and discuss the literature surrounding the potential effect of emerging technologies on the labour market, and how occupations, sectors and skills will be affected. The majority of the current literature focuses on the impact of AI on the labour market. AI is the current leading emerging technology, with the expected largest impacts on aggregate labour markets.

The majority of studies discussing the impact of AI on the labour market utilise the methodology developed by Felten et al. (2021). Felten et al. developed the AI Occupational Exposure (AIOE) measure, which uses a task-based approach to assign a relative score to the exposure of occupations to AI. These scores quantify the extent to which the tasks performed in a particular job can be enhanced or replaced by AI. For example, jobs involving repetitive cognitive tasks (e.g., data entry) received higher exposure scores compared to roles requiring creativity or manual dexterity (e.g., artists or construction workers).

Felten et al. (2021) found overall the highest-scoring occupations consist of white-collar occupations that require advanced degrees. They mapped occupational exposure scores to industries, and found that service industries that require a high level of information processing were most exposed- such as financial services, accounting, insurance and legal services. Meanwhile, the lowest-scoring industries are those that involve manual labour.

Top occupation by exposure	AI exposure score*
Chief executives, senior officials and legislators	91%
Teaching professionals	91%
Sales workers	90%
General and keyboard clerks	84%
Personal care workers	84%
Administrative and commercial managers	83%

Bottom occupation by exposure	AI exposure score*
Handicraft and printing workers	21%
Metal, machinery and related trades workers	16%
Drivers and mobile plant operators	12%
Food preparation assistants	11%
Labourers in mining, construction, manufacturing and transport	10%
Cleaners and helpers	6%

Felten's methodology discusses the exposure of occupations and industries to AI; however, it does not assign whether this exposure is more likely to have a displacement or augmentation effect - i.e. whether the role is likely to be enhanced by the use of AI or replaced by technology.

More recent studies have aimed to look further into how individual occupations and sectors will be affected by AI from both augmentation and displacement effects. ILO (2023) uses standard definitions of employment and uses GPT-4 to provide a description of the tasks in a role and a score based on how many of these tasks the GPT thinks it can perform. It then uses the mean score for a given occupation and its standard deviation to estimate whether jobs have greater potential for automation or augmentation. They suggest occupations that have a high mean but low standard deviation have a high potential for displacement, whilst those with high augmentation potential are those with a low mean score but high standard deviation, as technology can replace some of the tasks, but the overall role requires human performance.

They find that a range of clerical support workers, call centre workers, librarians and writers and application programmers have a high potential for automation. Meanwhile, roles which have high augmentation potential focus on professionals - including teachers, architects, medical practitioners, technicians and associate professionals. However, this approach still does not account for the desirability of AI to replace certain tasks.

Pizinelli et al. (2023) propose an alternative approach. They draw on the Felten et al. (2021) methodology, but use definitions of work contexts and “job zones” to assess the degree of complementarity. They suggest roles that have grave consequences for errors, like piloting an aeroplane or diagnosing diseases, are less likely to be assigned to AI without any human supervision. Additionally, they suggest occupations with high levels of education and training requirements or soft skills such as communication and human judgement are more likely to need humans to operate and integrate the knowledge needed to operate AI into the skillset of the occupation. Based on these criteria they adjust the Felten et al. (2021) AIOE measure to build a complementary-adjusted AI exposure measure. They suggest that moving away from a purely task-based approach helps account for the social, legal, and technical factors that will likely drive augmentation that are independent of exposure itself.

They find that some high-skill occupational groups with high exposure to AI, such as professionals and managers - including lawyers, judges and surgeons have the highest potential for augmentation. Meanwhile, clerical support jobs have high exposure but low complementarity, so they are most likely to be substituted.

It is difficult to predict precisely what will happen to the occupations and sectors that are most exposed to AI. Even the occupations which have primarily augmentation effects could face job losses, as whilst individuals become more productive through the use of AI, firms could decide to hold output constant and reduce their labour inputs. Additionally, the skills required within these occupations may change, with there being potentially greater value in the ability to operate and integrate technology within the occupation and the ‘softer’ skills the technology cannot replicate.

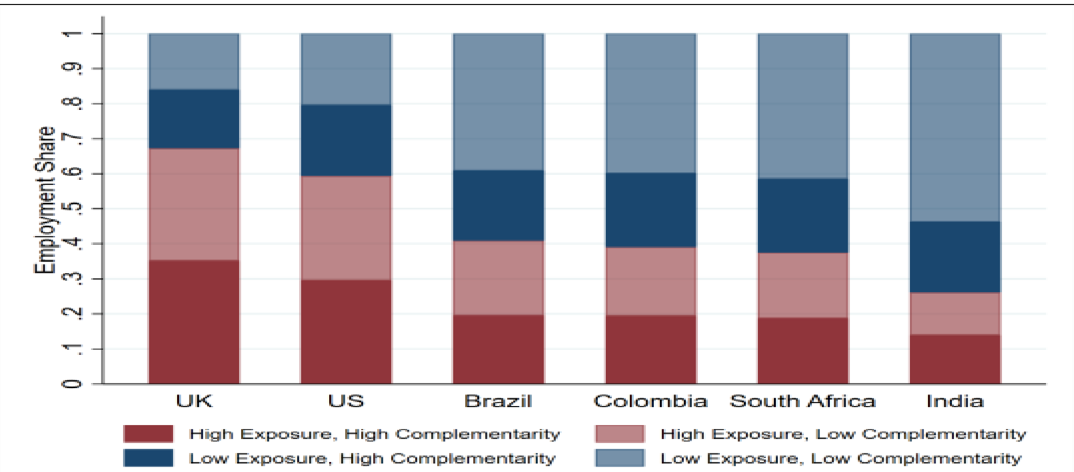
Meanwhile, new technologies will likely give rise to occupations and even industries which do not currently exist. As discussed by Autor (2022), 60 per cent of employment in 2018 in the United States was in jobs that did not exist in the 1940s. For example, following the introduction of the Internet, whilst demand for some clerical and administrative roles was reduced, a number of complementary industries have been created - including e-commerce, ICT services, social media and digital marketing. Additionally, Acemoglu and Restrepo (2018) found that about half of employment growth from 1980-2015 took place in occupations in which job titles or tasks changed. Overall, this provides potential reassurance that in the long run, the introduction and adoption of these technologies should not create widespread, long-lasting unemployment, and the economy will create new jobs to complement the new technologies.

However, whilst this will likely be the case in the long run, in the short run, there may be some transitional period of unemployment and skills mismatch. In addition, some sub-groups of society may be more affected than others. Therefore, it is important for governments to understand what industries and occupations will likely be exposed to ensure they have appropriate strategies in place to be ready for the impacts.

OVERVIEW OF THE LABOUR MARKET: UK AND INDIA'S POTENTIAL EXPOSURE

Pizinelli et al. (2023) apply their C-AIOE score to the UK, Brazil, India, Colombia and South Africa using labour force data from each country. They found that of these countries, the UK has the highest aggregate exposure level. Additionally, the UK has the highest score for workers engaged in highly complementary occupations - at 52 per cent, and the highest proportion of workers in occupations that have high exposure but low complementarity - at 32 per cent. India stands apart, with the lowest aggregate level of exposure. A total of 26 per cent of workers are in high-exposure occupations, divided into 14 per cent in occupations with high complementarity and 12 per cent in those with low complementarity.

Employment Share by AI Exposure and Complementarity



Source: Pizinelli et al. (2023)

The UK's high aggregate exposure is largely driven by the high proportion of the UK's workforce that are employed in professional occupations - nearly 30 per cent of the workforce, whilst the US has around 15 per cent. Meanwhile, the UK has a similar proportion of their workforce employed in the managerial sector as the US - 10.7 per cent to 14.4 per cent. India, the leftmost curve, exhibits the lowest levels of exposure due to its sizable worker population within the agricultural sector.

In EMs, the primary driver of lower AI exposure is the substantial proportion of workers in elementary occupations, a category characterized by low exposure levels. In India, this result is magnified by the extensive employment of workers in agriculture –over 30 per cent– which also falls under occupations exhibiting low levels of AI exposure (either in elementary occupations or in skilled agricultural workers).

The authors suggest that this means that whilst the UK will face large labour displacement effects, its workers are also more likely to gain from AI integration, potentially experiencing large productivity gains. Meanwhile, India faces lower exposure on both fronts, suggesting that India may face less short-run disruption but will also be less directly equipped to leverage the usage of AI technologies to enhance productivity without a deeper structural transformation of their economies.

However, despite a lower exposure, India is hub of AI skills - for example, Stanford University has ranked India among the top four countries along with the US, China, and the UK in the Global and National AI vibrancy ranking based on 42 indicators. GitHub, which is community of developers has ranked India at the top with the global share of 24 per cent of all projects.

A new Slack report, *State of Work*, highlights India as a global leader in AI adoption, with 75 per cent of surveyed desk workers integrating AI to enhance productivity. AI tools reportedly boost productivity by 53 per cent and save 3.6 hours weekly by automating routine tasks, equating to an extra working month annually for strategic work.

The India Workforce Hopes and Fears Survey 2023 highlights the transformative potential of AI on jobs in India, with 62 per cent of employees expecting significant skill changes in the next five years and 69 per cent aware of evolving demands (compared to 43 per cent globally). While 51 per cent see AI boosting productivity, 47 per cent anticipate learning new skills, and 37 per cent foresee job creation, challenges remain. One-third of Indian workers feel underconfident about reskilling (vs. 18 per cent globally), and 24 per cent believe AI could negatively impact their work—10 per cent higher than the global average. These insights underscore the urgent need for targeted upskilling to prepare India's workforce for AI-driven transitions.

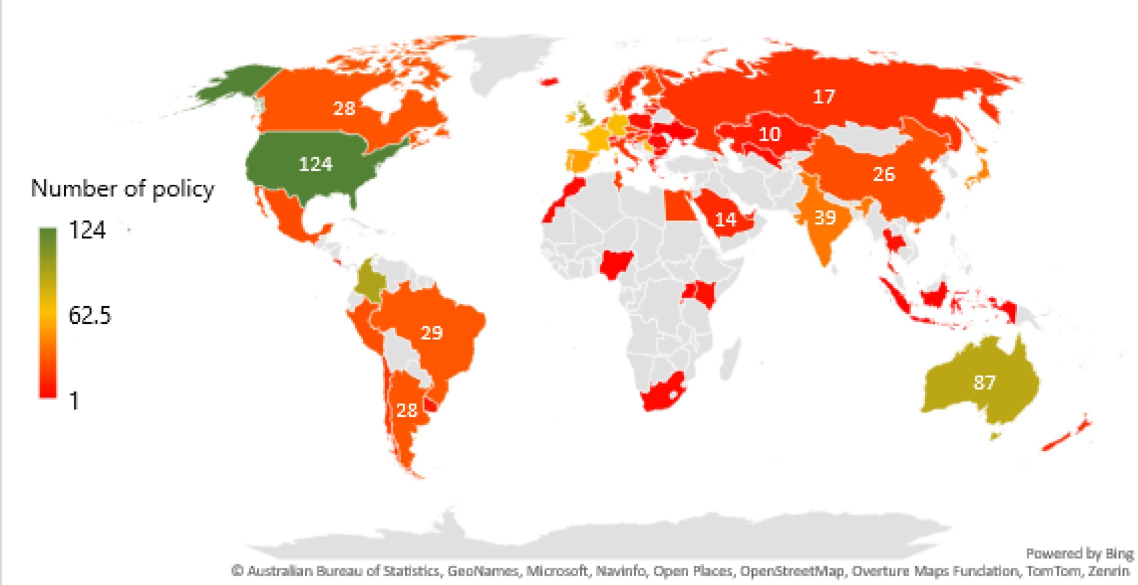
Current Policy Landscape

GLOBAL

The unveiling of national AI strategies by various countries marks a pivotal step in shaping the future of societies, economies, and governance. These strategies are driven by the need to address complex global challenges such as climate change and healthcare, offering AI-driven solutions for sustainable development. Additionally, they aim to boost economic competitiveness by fostering innovation and attracting investment, while also emphasizing ethical AI governance to ensure progress is responsibly managed. Successful AI strategies are built on principles of global collaboration, strong leadership, and immediate action to prioritize AI adoption over theoretical research. Notable global examples include the United States, which focuses on AI innovation and cross-sector collaboration; the European Union's emphasis on ethical AI and data governance; China's comprehensive plan for AI research and infrastructure; Canada's push for research excellence and AI startups, and Singapore's focus on responsible AI and workforce development. National AI strategies are, therefore, not just policy documents but integral to shaping the future of technology and global progress. Currently 71 countries and the EU together have around 1884 policies (OECD, 2025).

Countries adopt various governance models to coordinate national AI policies and ensure regulatory and ethical oversight. These models include assigning AI strategy oversight to existing ministries, such as those for information technology, economics, or education; creating new governmental or independent AI coordination bodies; establishing expert advisory groups to identify AI opportunities, risks, and challenges, and provide recommendations; and setting up oversight and advisory bodies focused on AI and data ethics. Each model aims to ensure effective implementation and responsible governance of AI technologies.

Chart : AI policy distribution across countries



Source : OECD AI repository

Source: An overview of national AI strategies and policies (Galindo et al., 2021)

SUMMARY OF THE UK'S AI POLICIES

The UK has a strong and growing AI sector, generating £14.2 billion pounds in revenue in 2023 alone. It contributed an estimated £5.8bn in Gross Value Added (GVA) to the economy in 2023, up from £3.7bn of GVA in 2022 (growth of 57%, more than 30 times faster than the rest of the economy).

Over the last decade, the UK has spent £2.8 billion on AI policy interventions. Central Government spending on AI has significantly increased in the last few years, from £20m per year in 2020 to over £300m annually in 2021 and 2022. In the last 3 calendar years, there have been ~140 AI-related contracts awarded by central Government bodies.

In 2025/26, the Department for Science Innovation and Technology's R&D budget is increasing to £13.5 billion. An additional £117 million in government funding was provided in 2023 for the AI PhD Centres for Doctoral Training programme, which will train over 1,500 doctoral students over the programme's lifetime.

The UK's **AI Opportunities Action Plan**, published on January 13, 2025, outlined a comprehensive strategy to harness artificial intelligence (AI) for economic growth, job creation, and improved public services. The plan emphasizes the importance of AI in driving productivity and positions the UK as a leader in AI innovation.

Key Policy Proposals include:

1. **AI Growth Zones** – The government is establishing AI Growth Zones, with the first in Culham, Oxfordshire, to accelerate AI infrastructure development and job creation in technology clusters.

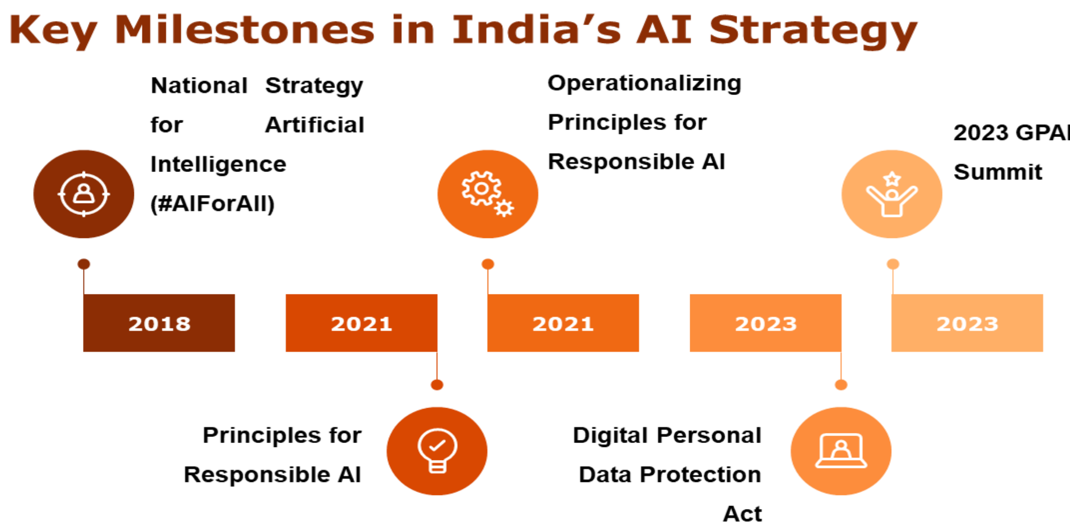
2. **Skills and Workforce Development** – Investment in AI-focused education, vocational training, and reskilling programs will ensure workers can integrate AI into their roles. The Skills England initiative will align education with industry needs to future-proof the workforce.

3. **Public Sector AI Integration** – A digital centre within the Department for Science, Innovation, and Technology (DSIT) will pilot AI-powered public services, improving efficiency and creating new roles in AI governance and implementation.

4. **Investment in AI R&D** – Increased public and private R&D funding, tax incentives, and university-business collaborations will strengthen AI innovation and support job creation in high-value sectors.

5. **AI Business Environment** – Policies promoting start-up support, regulatory clarity, and innovation-friendly policies will enhance AI adoption across industries and sustain employment growth.

SUMMARY OF INDIA'S AI POLICIES



The government is committed to harnessing the power of AI for sectors like healthcare, agriculture and education. At the same time, the Government is cognizant of the risks posed by AI.
The IndiaAI Mission was approved on 7th March 2024, a strategic initiative to establish a robust and inclusive AI ecosystem that aligns with the country's development goals. This mission is driven by a vision to position India as a global leader in artificial intelligence by focusing on seven foundational pillars.

The IndiaAI Mission, led by the IndiaAI Independent Business Division under Digital India Corporation, focuses on key initiatives focussed on skilling and employment are:

IndiaAI FutureSkills

Seeks to expand AI education through Data & AI Labs in Tier 2 and 3 cities and fellowships for 400 B.Tech and 500 M.Tech students. Top 50 NIRF-ranked institutes will onboard new PhD scholars. A model AI Data Lab has been established at NIELIT Delhi, with 27 more planned in collaboration with states.

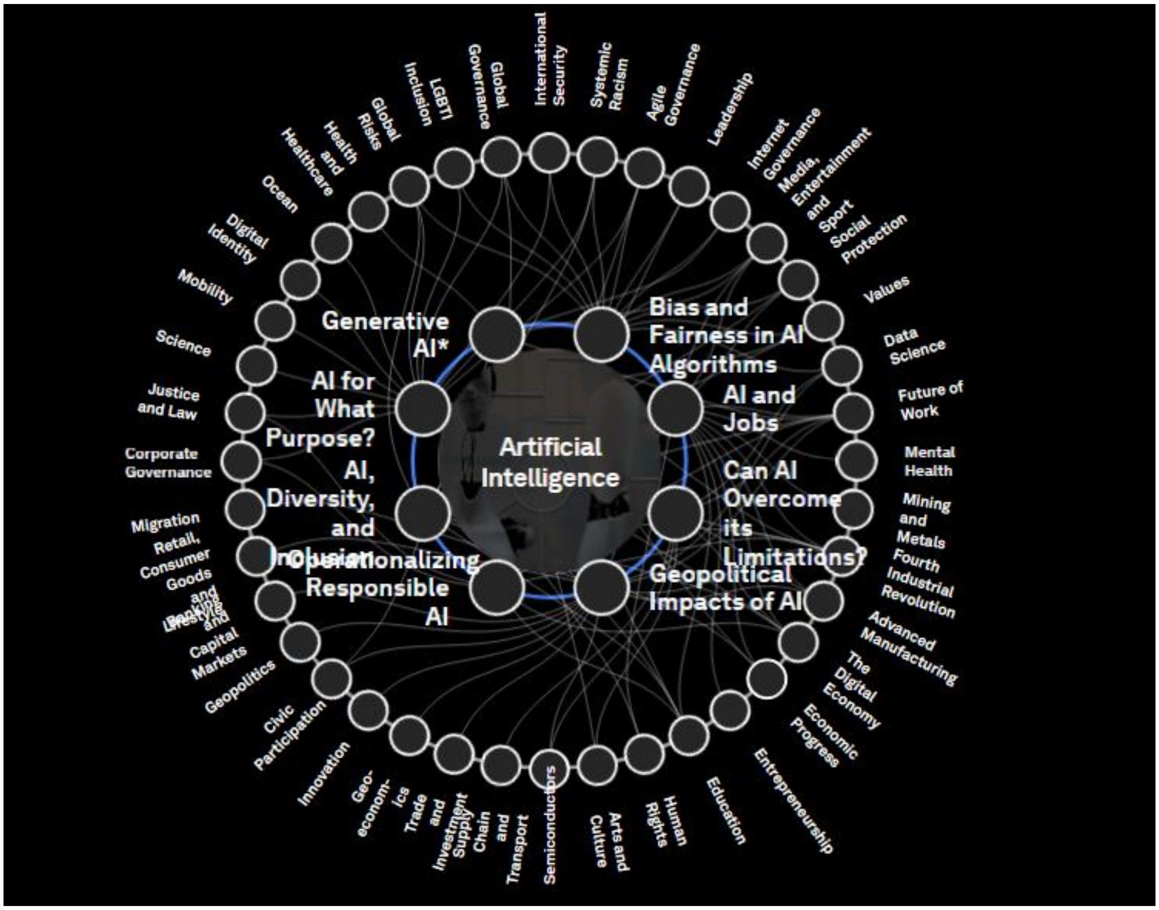
IndiaAI Startup Financing

Supports AI startups at Pre-Seed, Seed, and Growth stages, with multiple stakeholder consultations held.

Safe & Trusted AI

Promotes responsible AI development with eight selected projects addressing AI bias, explainability, privacy, and governance. NASSCOM and industry stakeholders are drafting voluntary guidelines for safe AI deployment.

Strategies for policy making



AI and emerging technologies are expected to generate substantial productivity gains, with positive implications for economic growth. However, these benefits will not be evenly distributed across sectors, occupations, and skill levels, potentially exacerbating labor market disruptions and widening economic disparities (Korinek and Stiglitz, 2017). High-skilled industries and technologically advanced economies may capture a disproportionate share of AI-driven productivity gains, while others risk being left behind (Pizinelli et al., 2023). A structured policy framework can play a role in shaping AI's distributional effects, balancing trade-offs between growth, employment, and equity objectives while considering broader macroeconomic constraints.

These choices are further constrained by fiscal and policy considerations. Public investment in AI-related infrastructure, skills development, and social protections competes with existing spending priorities, particularly in economies with limited fiscal space. AI policy also interacts with industrial, labor market, and welfare policies, requiring coordination across government departments. The extent to which governments allocate resources to AI policy will depend on national policy frameworks and economic conditions. This underscores the role of AI policy within a broader set of trade-offs, where technological advancement, fiscal constraints, and existing policy commitments interact. The following section outlines a framework for governments to consider how to maximise gains from AI, which they can apply to their individual priorities and economic environments.

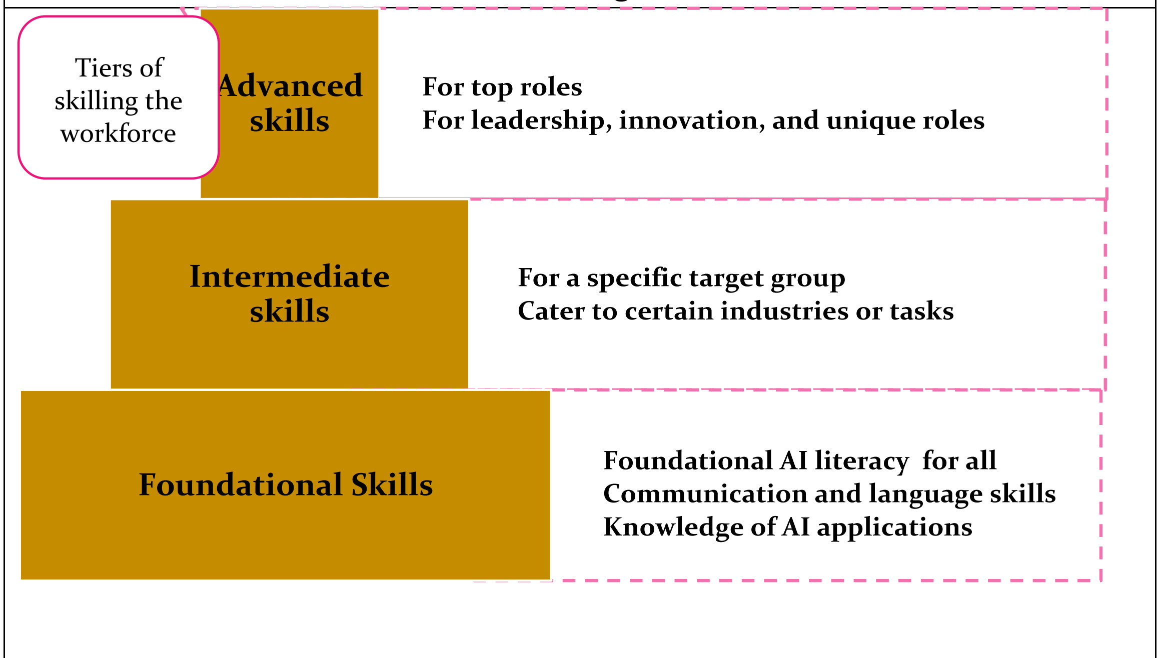
SKILLS

Skills policy helps prepare the workforce for the future labour market. By ensuring the workforce has the right balance of skills, governments can help mitigate potential negative effects associated with emerging technologies and job displacement, and promote productivity growth through improving human capital and labour composition. However, many countries already face skills mismatch - where the composition of skills does not effectively meet industry needs - workers may be over or underqualified for the jobs available, or not have qualifications in the right areas. An effective strategy for skills will help reduce these issues, and ensure that they are not exacerbated by emerging technologies' impact on the structure of the labour market and the new skills required.

Rather than focusing narrowly on skilling for specific "AI jobs," policymakers may wish to consider a broader understanding of how tasks within various roles are likely to be impacted by AI and other emerging technologies. As these technologies evolve, the notion of discrete "AI jobs" may diminish, giving way to a labour market where AI is integrated across a wide range of occupations. automating some while enhancing the efficiency of others (Felten et al., 2021; Pizinelli et al., 2023). This underscores the importance of designing skills strategies that consider the evolving nature of work and task augmentation.

A layered approach to skills strategy provides a framework for meeting the diverse needs of industries and workers. The basic three tiers of the skill strategy are elaborated in chart below.

Chart: Skills Pyramid: Tiered framework for AI upskilling, reskilling and new skilling



High-skilled AI work

With the influx of new technologies, it is likely that digital and technological skills will be in greater demand. Some of these may have high-skill requirements, such as skills related to the development and maintenance of AI systems – such as programming, coding, data management and analytics, and robotics. The demand for specialised AI skills has been rising – in the US demand for AI skills was found to have grown 4 times over the period from 2010 to 2019 – particularly in the Information sector, but also Professional Services, Administrative Support Services and Finance sectors (Alekseeva et al., 2021). Job postings that demanded AI-related skills were found to have an 11 per cent wage premium within the same firm and 5 per cent premium within the same job title. These roles are highly skilled – the OECD found that in 2019 two-thirds of the AI workforce has a tertiary degree, whilst 38 per cent of the average employed workforce had a tertiary degree (Green and Lamby, 2023).

Whilst employment growth in the AI sector is high and the level of earnings are higher than average in AI jobs, studies have found wage growth has been more muted. A study by the OECD found that wages grew cumulatively by 7 per cent for the AI workforce compared to 9 per cent overall over the period 2017 to 2019 (Lane, Williams and

Broecke, 2023). The authors suggest this means the supply of workers in the AI occupations may be keeping up with demand.

Current evidence does not suggest there are major shortages in high-skilled AI occupations globally, which implies government intervention to increase the provision of these skills may not be required, however, as AI development and adoption increases, growth in employment demand could start to exceed supply. Overall, this suggests governments should continue to monitor the demand and supply of AI occupations. They may also wish to work with industry and higher education to ensure current and future courses meet employer and industry needs. Policymakers may wish to also consider how to best integrate work placements and apprenticeships to help maximise long-term employment following education and training.

Digital skills

As discussed in the first section, emerging technologies are likely to impact a variety of occupations, not just those directly related to the development and maintenance of technological systems. This involves intermediate skills, such as applying AI to specific use-cases, and basic skills, including the ability to operate AI systems or applications. Emerging technologies will likely augment many occupations, changing the composition of tasks and potentially increasing productivity. However, this means the skills requirements within occupations may change and effective adoption and usage of technology will be required to maximise potential productivity benefits. Rigley et al. (2024) found that countries that emphasised a broader, nationwide approach to upskill and educate all citizens at different levels had higher AI readiness and index scores than countries that focussed on a narrower, expert-driven approach. The authors suggest that future AI skills policy should follow broad, nationwide approaches to upskill and educate all citizens at different levels of AI expertise.

AI adoption is still relatively low – in the UK only 20 per cent of businesses are currently using AI. In a recent OECD survey of employers and workers, 40 per cent of employers declared that lack of relevant skills was a barrier to AI adoption. Meanwhile, even amongst firms adopting AI, demand for training in AI is high – with nearly 75 per cent of users saying they were enthusiastic to learn more.

Overall, this suggests that there is likely demand for elementary and intermediate knowledge of AI and how to use it – ‘AI literacy’. As the technology continues to develop and the potential applications increase this is likely to be in greater demand, and help ensure firms and countries harness the positive effects of new technologies. Additionally, as tasks within occupations change, training may help reduce potential job losses for those who do not possess these skills – particularly in occupations that have a high proportion of tasks that may be automated.

Emerging technologies are expected to reshape skills requirements across sectors, with implications for workforce development and training policy. Several areas have been identified in the literature as key to supporting AI adoption and mitigating potential disparities in skills access.

- **AI literacy in primary and secondary education** – Integrating AI education into the school curriculum could help build foundational skills and improve AI readiness.
- **Public awareness** – Awareness campaigns can support understanding of AI's potential applications, to help increase adoption.
- **Lifelong learning and workforce adaptation** – As AI adoption progresses, demand for reskilling is likely to increase. There is a growing focus on continuous learning frameworks, with initiatives to integrate AI into workforce development strategies.
- **Employer incentives for AI training** – Emerging technologies may require a greater focus on lifelong learning, however, costs are frequently cited as the biggest barrier to training – particularly amongst small businesses. To maximise productivity gains and reduce the likelihood of groups being left behind governments should promote research in how to effectively promote and incentivise training, including exploring grants and subsidies.
- **Sector-specific training needs** – AI's impact on job tasks varies by industry, requiring tailored training approaches. Governments may wish to promote research into understanding industry specific requirements and how to effectively plan training courses.

Other skills

Whilst emerging technologies are expected to displace some skills and jobs, there remain a number of skills and occupations that technology either cannot replicate, or there might not be the demand for technology to do those tasks or occupations. These include soft skills, such as communication, emotional intelligence, creativity, innovation and ethical reasoning (Pizinelli et al., 2023). Governments and businesses may wish to consider how to ensure students and the workforce are adequately equipped with soft and practical skills, as technology is unlikely to be able to replace these.

Additionally, emerging technologies are not the only future challenge that governments face, and strategies should be considered in tandem with other potential structural changes in the economy. For example, many countries face demographic changes and ageing populations, which come with associated challenges and demands - including increased care requirements and demand for healthcare. Many advanced economies including the UK are already facing shortages of carers and other associated occupations such as physiotherapists and nurses (Health Foundation, 2023). These occupations require physical and emotional skills which mean they are unlikely to be able to be done entirely by technology. The green transition is another challenge policymakers will continue to face, and demand may increase for occupations and skills to support this transition. Governments should develop skills strategies and policies in tandem with horizon scanning, to help ensure the skills of the workforce meet future needs.

WELFARE AND EMPLOYMENT POLICY

As discussed in section 1, the effect of emerging technologies on unemployment is uncertain, and likely to differ by skill-level and sector. However, it is likely that the workers exposed may be of a higher skill level than previous periods of technological change and a different composition of skills will be required.

At this stage of technological development it seems unlikely technology will create mass unemployment. Whilst the composition of tasks within jobs will likely change, in many roles technology will augment the role and workers will still be required to operate technology and carry-out cognitive or physical tasks. Additionally, in the long-run, it appears likely that emerging technology will create new, potentially higher productivity, jobs to replace those that have been displaced, as seen in previous periods of technological change. Nevertheless, in the transition period certain workers and sub-groups of society may be more exposed and find that their skill-set is no longer in demand.

Additionally, economic growth alone is not necessarily sufficient to improve labor market outcomes, as evidenced by India’s persistent employment challenges despite sustained high growth over the past two decades (Sher V., 2018). Social protection remains central to this discussion, with policies ensuring basic social security guarantees forming a critical component of AI governance and future-of-work strategies (IMF, 2024). When designing AI strategies governments may wish to consider how safeguard workers' economic security and job quality

To prevent long-term unemployment of workers in displaced occupations, governments may wish to consider an integrative approach to social welfare and skill provision. Job centres and employment offices may wish to place greater focus on providing support and education in reskilling displaced workers, in line with wider skills strategy. In addition, in line with wider economic goals governments should ensure there are appropriate incentives to reward work and the social safety net assists workers in transitioning to new roles within the evolving economy.

Additionally, governments may wish to consider how AI may impact those in work. Technological advancements in the last decade, such as the rise of the platform economy, whilst some argue it creates opportunities for marginalised workers (Hoang et al., 2020), others suggest it has negative effects on job quality and employment rights (Bogliacino et al., 2020). Governments may wish to consider if their frameworks of social protection and employment regulation are adequately structured to mitigate potential job quality deterioration, safeguard workers' rights, and ensure that the benefits of technological advancements—such as those seen in the platform economy—are equitably distributed rather than deepening labor market vulnerabilities. For example, The Decent Work Agenda, as outlined by the International Labour Organization (ILO), provides a basis for balancing economic growth with worker protections, ensuring that technological progress translates into sustainable employment rather than exacerbating vulnerabilities in the labor market.

INDUSTRIAL POLICY:

Countries' individual environments will impact their emerging technology strategies. For example, growth and productivity gains from emerging technology may come from the benefits associated with the adoption of emerging technologies or, in addition, the economic benefits associated with the development of technologies themselves. New businesses and start-ups related to emerging technologies could provide opportunities for growth. For example, in the United States, AI-driven productivity growth has been concentrated in the technology sector, which has played a pivotal role in driving economic expansion over the last decade (Aghion & Bunel, 2024).

However, in order to maximise productivity gains and job creation, whilst minimising costs, governments should consider the broader business, industrial and macroeconomic environment of their country (Korinek, 2024). Governments may wish to analyse where they have existing strengths, including looking at industries, skills and the labour force when considering how to develop their AI strategies. Targeting areas where there are existing strengths helps maximise existing capabilities and skills. Therefore, industrial policy could evolve to support AI integration across various sectors. This involves a multifaceted approach that addresses the diverse impacts of AI on different industries. Key strategies include:

- **Encouraging AI Adoption:** Productivity gains depend on the adoption of new technologies, and individuals and businesses face multiple barriers to adopt - including economic constraints, technical barriers, resistance to change and implementation challenges. Governments may wish to prioritise research into effective incentives and strategies to encourage adoption. These may include financial incentives, training and awareness and regulatory or policy support.

- **Facilitating Dissemination**: To maximize the benefits of AI, it is crucial to ensure that efficiencies gained through AI adoption are reflected throughout production & supply chains. This requires policies that encourage knowledge sharing, standardization, and AI integration across all production and distribution levels.

- **Recognizing AI as a General-Purpose Technology:** AI's broad applicability means that its impact will extend beyond specific sectors. Industrial policy should acknowledge AI's potential to drive systemic changes in the economy, influencing everything from healthcare and education to finance and transportation.

- **Flexibility and Adaptability**: Industrial policy must be flexible and adaptable to keep pace with technological change. This involves continuous monitoring of technological trends, regular updates to policies, and the ability to quickly respond to emerging opportunities and challenges.

- **Investment in R&D**: Sustained investment in research and development is critical to maintaining a competitive edge. Policies should support innovation through funding for R&D projects, collaboration between academia and industry, and incentives for private sector investment in new technologies.

- **Business Environment:** Governments should explore strategies to foster competition and dynamism across sectors, if they wish to enable or promote the growth of emerging technology related start-ups. This may involve offering financial support through start-up grants, subsidies, or tax and R&D incentives, as well as lowering entry barriers via regulation and competition policy. Furthermore, governments should consider strengthening the broader entrepreneurial ecosystem by providing incubators and accelerators, facilitating access to talent, and ensuring availability of finance and markets. Policies on competition and R&D should be designed to incentivize and reward the research and development of innovative technologies, while also creating opportunities for new businesses to enter and leverage technology in groundbreaking ways (Aghion and Bunel, 2024).

As industrial policy adapts to the realities of AI, the focus will be on using R&D support, skills development, and technological standards to foster growth across different sectors. By aligning AI advancements with industrial policy objectives, governments can help effectively drive economic growth and adapt to the AI transition.

INTERNATIONAL COOPERATION

The international landscape of artificial intelligence (AI) in the 21st century is marked by a strong spirit of collaboration, particularly in the areas of research, innovation, and standardization. There are compelling reasons to promote and enhance this international cooperation. AI research and development is becoming increasingly complex and resource-intensive, where scale plays a significant role as an advantage. By fostering cooperation among governments, AI researchers, and developers across borders, one can maximize this advantage and utilize comparative strengths for the benefit of all. Without international collaboration, there is a risk of creating competitive and redundant investments in AI capabilities, resulting in unnecessary costs and subpar outcomes for individual governments. Several crucial inputs for AI development—such as access to high-quality data (especially for supervised machine learning), large-scale computing resources, expertise, and talent—benefit greatly from the scale.

- International cooperation grounded in shared democratic principles for responsible AI can help ensure focused development and build mutual trust.
- The next steps in AI governance involve turning AI principles into actionable policies, regulatory frameworks, and standards. This process will require a deeper understanding of how AI functions in practice and careful navigation of principles within specific contexts, especially when facing inevitable trade-offs, such as balancing accuracy and explainability in AI systems.
- To achieve effective cooperation, we will need to take concrete steps in targeted areas, as outlined in the recommendations of this report.

REGULATION:

When it comes to regulation, differing approaches can create barriers to innovation and diffusion. Government efforts to promote domestic AI development based on concepts of digital sovereignty can lead to negative consequences such as restrictions on data access, data localization, discriminatory investment practices, and other regulatory requirements.

Similarly, varying risk classification systems and regulatory conditions can increase costs for businesses trying to operate in the global AI market. Different government regulations may require companies to develop multiple versions of AI models, which can complicate the process of building an AI system and lead to higher compliance costs—burdens that disproportionately impact smaller firms. These diverging regulations may also necessitate variations in how data sets are collected and stored, adding complexity to data systems and reducing the overall utility of data for AI applications. These additional costs can affect not only AI-as-a-service offerings but also hardware-software systems incorporating AI solutions, such as autonomous vehicles, robots, and digital medical devices.

Enhanced cooperation is essential for creating a larger market where countries can leverage their competitive advantages. For instance, the EU aims to gain a competitive edge in "industrial AI," allowing European enterprises to utilize AI without the need for significant reengineering to meet the requirements of other jurisdictions.

Aligning key aspects of AI regulation can enable specialized firms to thrive in AI development. These companies generate business by focusing on specific AI systems and then licensing them to other firms as part of a broader toolkit. As AI becomes more prevalent, complex stacks of specialized AI systems are likely to emerge across various sectors. A more open global market would allow a company to utilize digital supply chains, combining products like a natural language model developed in Canada, a video analysis algorithm from Japan, and network analysis techniques created in France. Fostering global competition among these specialized firms will encourage healthier markets and drive further AI innovation..

TRADE:

Global cooperation in trade and data governance is central to maximizing the benefits of AI diffusion. Restrictions on the flow of goods and data—whether driven by industrial policy or strategic concerns over sovereignty—risk disrupting global value chains, reducing market size, and limiting incentives for investment in AI. While efforts to map and reduce dependencies on foreign technology are a rising component of industrial strategies in many economies, protectionist measures may weaken cross-border collaboration and constrain AI adoption (Brookings Institution, 2024).

AI has the potential to address global challenges, but no country can fully harness these benefits in isolation. Data sharing and cross-border AI applications are particularly relevant for areas such as climate change mitigation and pandemic preparedness. Several governments, including those involved in the Framework for Cooperation on Artificial Intelligence (FCAI), have expressed interest in deploying AI for social, humanitarian, and environmental objectives. The EU's Green Deal includes AI-driven initiatives to support sustainability, while the G-7 and Global Partnership on AI (GPAI) have emphasized AI's role in achieving the U.N. Sustainable Development Goals (Global Partnership on AI, 2024). Collaborative AI "moonshots" may facilitate joint research efforts, leveraging AI in fields such as healthcare, climate science, and agriculture while also providing a platform for testing responsible AI governance.

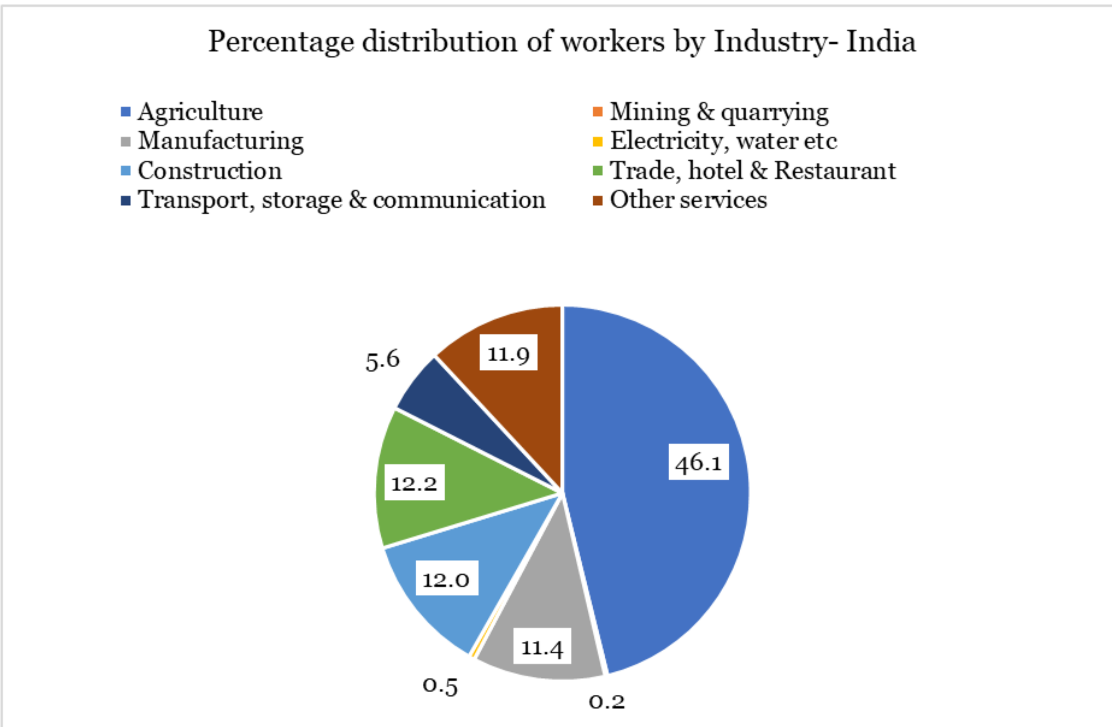
International alignment is also relevant in maintaining open markets and protecting democratic values. AI governance varies across countries, and the use of AI by techno-authoritarian regimes raises concerns about human rights and digital fragmentation. The divergence in AI regulatory approaches risks creating incompatible technology ecosystems and fragmenting global AI research and development (Brookings Institution, 2024).

The inclusion of international cooperation in most national AI strategies reflects an understanding that AI innovation is closely tied to cross-border collaboration. Ensuring open access to data and maintaining cooperation in AI research and governance will likely remain a priority for governments seeking to balance national security interests with the economic and societal benefits of AI diffusion (CIGI, 2024).

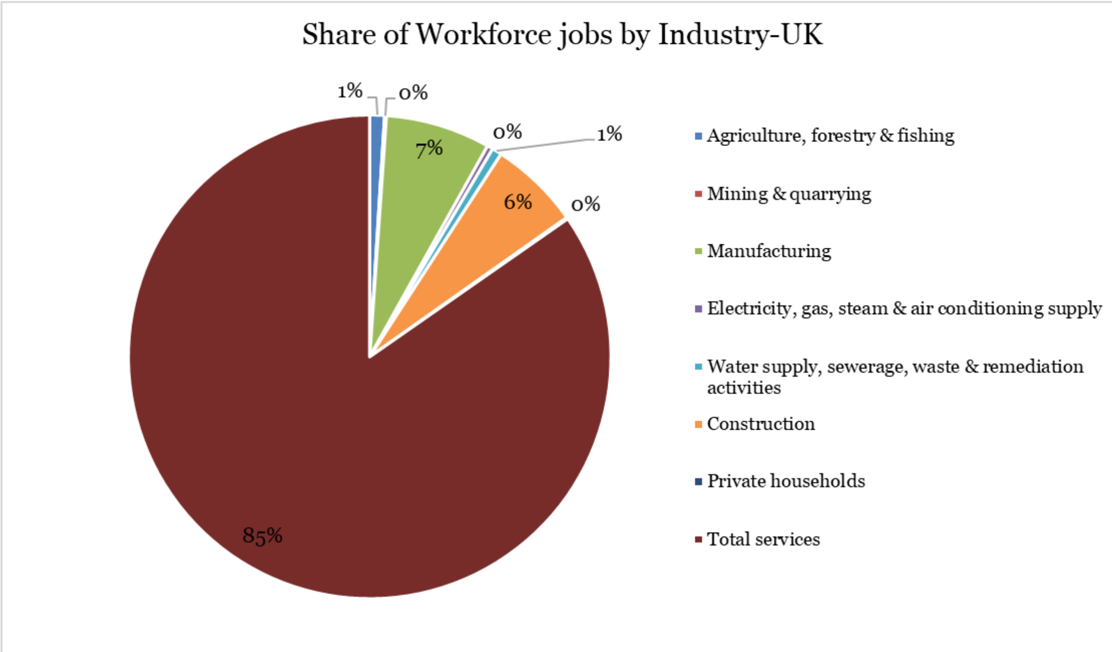
Comparison between the labour market in India and UK

While the Indian labour market is agriculture dominated, the UK has a larger share of its workforce employed in services. Agriculture being the primary occupation of the majority of the working population in India, it reduces the exposure of the workforce to technological changes. With a greater share of the UK's workforce involved in the services sector, the workforce has a higher exposure to technological advancements.

Chart: Distribution of workforce by industry- India & UK



Source: Annual PLFS report, MoSPI, India (2023-24)



Source: Office of National Statistics, UK Government (September 2024)
Note: Total services includes wholesale, transport, accommodation and food, information, & communication financial, insurance and real estate, professional & scientific, administration, public administration and defence, education, health and social care, arts and entertainment and other services sectors.

This distinction between the labour markets of the two countries is important to understand the policy priorities of the two countries.With limited workforce exposure to AI, India has an opportunity to catch up—or even lead—by preparing its workforce for future changes. Education and skilling will be key to human-centric AI adoption while minimizing labour displacement. For the UK, with higher exposure to AI, the policy needs to focus on an integrative approach to ensure social welfare of the displaced workers, focusing on reskilling and upskilling the workforce to make the transition smoother.

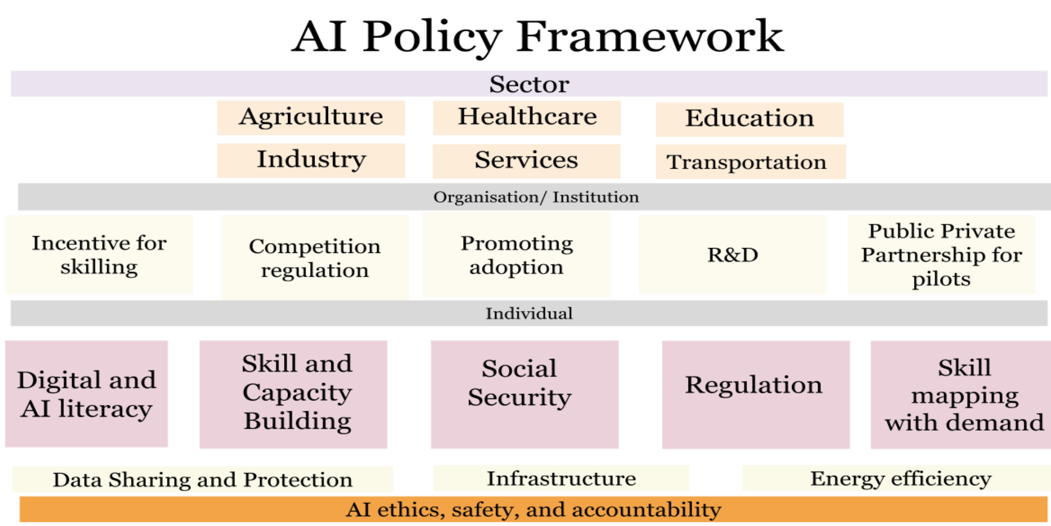
Given the ever-evolving nature of technological change, it is crucial for both countries to prioritize research and development (R&D), as well as the adoption and dissemination of new technologies. Policy measures should ensure that technological adoption is not restricted to a select few firms. Regulatory and industrial policies will play a key role in fostering competition and promoting widespread adoption of productivity-enhancing technologies, ultimately driving overall economic growth.

AI POLICY FRAMEWORK

The AI policy framework of a country is shaped by its development priorities, labour market structure, and overall economic landscape. This paper proposes a tiered framework, where each tier represents a distinct target of the policy. Every AI policy is envisioned to have at least three tiers: the sector of focus, the organizations or institutions within that sector, and, at the base, the individual.

In the case of India, while the majority of the workforce is employed in agriculture, the services sector contributes the largest share to GDP. As shown in the figure, AI policy interventions vary by sector. For agriculture, policies would focus on enhancing productivity, given that agricultural workers have limited exposure to technological change. In contrast, AI policy for the services sector must address both productivity and workforce development, considering the sector's greater technological integration.

Meanwhile, over 80% of the UK's workforce is employed in the services sector (ONS, 2025), meaning the UK has one of the highest global exposures to AI (Pizinelli et al., 2023). This positions the UK well to maximise productivity gains from the adoption of new technologies, should be considered in tandem with skills development and retraining to minimise potential negative displacement effects.



Beyond sector-specific interventions, certain foundational enablers—such as data sharing and protection, the development of adequate infrastructure to support technology adoption and diffusion, and the efficient use of energy—are critical across all tiers and sectors. While the timing and scale of investment in these areas may vary based on national priorities, they remain essential for an effective AI policy framework.

The diagram categorizes key policy interventions across the three tiers. The selection of these interventions depends on a country's priorities, labour market characteristics, and economic structure.

KEY PILLARS OF THE POLICY FOR INDIA

AI policy for India should be people-centred and focused on long-term benefits while addressing the challenges AI poses. Key characteristics include:

- **Evidence-Based Investment**: There is need for evidence of generative AI's utility before committing large public investments. It is essential to avoid speculative investments in computational power and data centers, considering their resource intensity and potential short-lived impact on AI's future development.
- **Reducing Deployment Harm:** The government must ensure that AI deployment does have a negative impact on individuals or society. This includes clarifying liability for AI-induced harm, especially in sectors like healthcare, and addressing cybersecurity risks. Strengthening legal frameworks to handle issues of data protection, AI malfunction, and competition concerns is crucial.
- **Reclaiming Digital Public Infrastructure (DPI):** There is a need to leverage the developed DPI, which refers to open, interoperable digital systems, to prevent the monopolization seen in big tech platforms. This would promote competition, with public control over the essential digital infrastructure that enables equitable access to services. Policies should encourage non-monopolistic digital market models while fostering innovation and public oversight.
- **Broadening AI Policy**: The policy should not be restricted to deep learning and large language models, which dominate the global AI landscape. India's AI policy should foster diverse AI development approaches, investing in risky but potentially rewarding research beyond conventional models.

This comprehensive policy approach would balance technological progress with ethical, legal, and social considerations, ensuring AI's benefits are widely shared and sustainable in India.The evolving transformations of the labour markets worldwide revolve around the need for skilled workers, AI-ready workers, and workers who are ready even before they formally enter the job markets.

KEY PILLARS OF POLICY FOR THE UK

The UK is highly exposed to AI due to its services-heavy employment structure. At the same time, boosting growth and productivity is a central mission of the UK government. To harness AI's full potential, the government must prioritize skills development, industrial strategy, and widespread AI adoption. However, current AI adoption remains low, with only 20% of UK businesses and 10% of SMEs integrating AI technologies (OECD, 2024), significantly lagging behind global leaders.

- **AI Education and Digital Literacy**: Embed AI and digital literacy in primary, secondary, and tertiary education to equip future generations with essential skills.
- **Employer-Led Training Incentives**: Invest in research on the effectiveness of tax relief and grants to support employer-driven AI skills development, ensuring continuous reskilling and lifelong learning.
- **Investment in AI Startups and R&D**: Expand government-funded initiatives to drive AI innovation through university partnerships and industrial collaborations.
- **Business Environment and Start-Up Growth**: Promote research into strategies that foster competition and dynamism across sectors, assessing the effectiveness of financial support, regulatory policies, and ecosystem development measures such as incubators, accelerators, and improved access to talent, finance, and markets.
- **AI Adoption in Key Sectors**: Develop and implement research-backed financial incentives, awareness campaigns, and training programs to accelerate AI adoption across industries.
- **Public Sector AI Implementation**: Encourage AI-driven automation to enhance government efficiency and streamline operations.
- **Evidence-led policy:** Given limited fiscal space, AI policies should be evidence led. Additionally, policies should be considered against other key priorities.

A dynamic and adaptive AI policy must balance economic growth with workforce resilience, ensuring that the UK remains competitive in an AI-driven global economy. Focussing on skills development, encouraging AI adoption and promoting a dynamic and competitive business ecosystem will help the UK maximise potential growth benefits whilst reducing employment risks.

References

Acemoglu, D. (2025). *The simple macroeconomics of AI.* Economic Policy, 40(121), pp.13-58. Available at: w32487.pdf

Acemoglu, D. and Restrepo, P. (2018). *The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment.* American Economic Review, 108(6), pp. 1488–1542.

Aghion, P. and Bunel, M. (2024). *AI and Growth.* Federal Reserve Bank of San Francisco. Available at: https://www.frbsf.org/wp-content/uploads/AI-and-Growth-Aghion-Bunel.pdf

Alekseeva, L. et al. (2021). *The demand for AI skills in the labor market.* Labour Economics, Vol. 71, p. 102002. https://doi.org/10.1016/j.labeco.2021.102002

Autor, D. H. (2022). *The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty.* NBER Working Paper No. w30074. Available at SSRN: https://ssrn.com/abstract=4122803

Autor, D. H. and Dorn, D. (2013). *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.* American Economic Review, 103(5), pp. 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Bogliacino, F., Codagnone, C., Cirillo, V., Guarascio, D. (2020). *Quantity and Quality of Work in the Platform Economy*. In: Zimmermann, K. (eds) Handbook of Labor, Human Resources and Population Economics. Springer, Cham. https://doi.org/10.1007/978-3-319-57365-6_18-1

Brookings Institution (2024). *Strengthening international cooperation on AI.* Available at: https://www.brookings.edu/articles/strengthening-international-cooperation-on-ai/

Brookings Institution (2024). *Toward international cooperation on foundational AI models.* Available at: https://www.brookings.edu/articles/toward-international-cooperation-on-foundational-ai-models/

Centre for International Governance Innovation (CIGI) (2024). *Trade agreements and data governance.* Available at: https://www.cigionline.org/articles/trade-agreements-and-data-governance/

Felten, E., Raj, M., & Seamans, R. (2021). *Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses.* Strategic Management Journal, 42(12), pp. 2195–2217. https://doi.org/10.1002/smj.3286

Galindo, L., Perset, K. and Sheeka, F. (2021). *An overview of national AI strategies and policies.* OECD Going Digital Toolkit Notes, No. 14. OECD Publishing, Paris. https://doi.org/10.1787/c05140d9-en

Global Partnership on AI (GPAI) (2024). *Climate change and AI.* Available at: https://www.gpai.ai/projects/climate-change-and-ai.pdf

Goos, M., Manning, A. and Salomons, A. (2009). *Job Polarization in Europe.* American Economic Review, 99(2), pp. 58–63. https://doi.org/10.1257/aer.99.2.58

Green, A. and Lamby, L. (2023). *The supply, demand and characteristics of the AI workforce across OECD countries.* OECD Social, Employment and Migration Working Papers, No. 287. OECD Publishing, Paris. https://doi.org/10.1787/bb17314a-en

Health Foundation (n.d.). *The social care workforce crisis.* The Health Foundation. Available at: https://www.health.org.uk/features-and-opinion/blogs/social-care-workforce-crisis

Keynes, J. M. (1930). *Economic Possibilities for our Grandchildren.* In: *Essays in Persuasion.* New York: Harcourt Brace, pp. 358-373.

Lane, M., Williams, M. and Broecke, S. (2023). *The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers.* OECD Social, Employment and Migration Working Papers, No. 288. OECD Publishing, Paris. https://doi.org/10.1787/ea0a0fe1-en

Pizzinelli, C., Panton, A., Mendes Tavares, M., Cazzaniga, M. and Li, L. (2023). *Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications.* IMF Working Paper No. 2023/216. Available at SSRN: https://ssrn.com/abstract=4612697

Schwab, K. (2016). *The Fourth Industrial Revolution: What it means and how to respond.* World Economic Forum. https://www.weforum.org/stories/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

Smolny, W. (2003). *Innovations, Prices and Employment: A Theoretical Model and an Empirical Application for West German Manufacturing Firms.* Available at: https://doi.org/10.1111/1467-6451.00076

Strengthening international cooperation on AI. Available at: https://speevr.com/2021/10/25/strengthening-international-cooperation-on-ai-2/

Verick, S. (2018). *The Puzzles and Contradictions of the Indian Labour Market: What Will the Future of Work Look Like?* IZA Discussion Paper No. 11376. Available at SSRN: https://ssrn.com/abstract=3137507

Vivarelli, M. (2012). *Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of the Literature.* IZA Discussion Papers 6291, Institute of Labor Economics (IZA).

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