



GEN-AI: ARTIFICIAL INTELLIGENCE AND THE FUTURE OF WORK

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Cazzaniga, M. F. Jaumotte, L. Li, G. Melina, A. J. Panton, C. Pizzinelli, E. Rockall, and M. M. Tavares (2023). *Gen-AI: Artificial Intelligence and the Future of Work*. Staff Discussion Note. SDN/2024/001. International Monetary Fund, Washington, DC.

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Focus

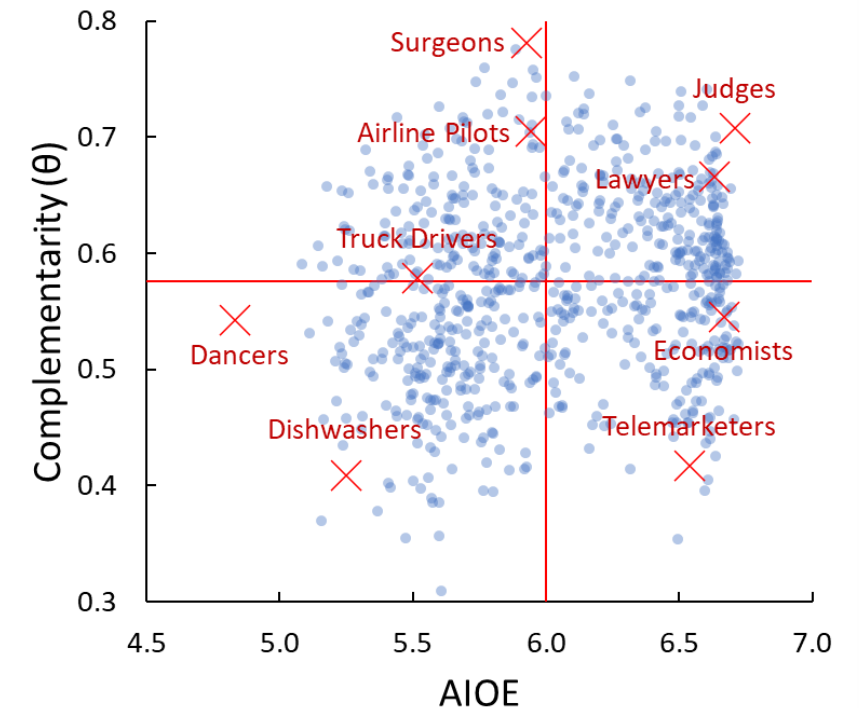
- Artificial Intelligence (AI) is set to profoundly change the global economy
- What are the implications for the future of work?
- The report examines:
 - implications of AI adoption on jobs across AEs and EMDEs
 - its potential to displace and complement human labor
 - potential effects of AI on inequality and productivity
 - countries' preparedness to adopt AI

AI Exposure and Complementarity

Measuring exposure to and complementarity with AI

- **Exposure to AI:** Degree of overlap between AI applications and human abilities in occupations (Felten et al., 2021;2023).
- **Shielding → Complementarity Potential:** Leverages two parts of the O*NET capturing “work context” and “skills.” Group into 6 categories:
 - **a. Communication:** Face-to-Face, and public Speaking
 - **b. Responsibility:** Responsibility for outcomes and others’ health
 - **c. Physical Conditions:** Outdoors exposed, and physical proximity
 - **d. Criticality:** Consequence of error, freedom and frequency of Decisions
 - **e. Routine:** Degree of automation, and unstructured vs structured Work
 - **f. Skills:** Job zone (level of education, training and skills needed)
- **Examples:**
 - Judges: High AI exposure yet shielded by societal norms and laws—AI may complement their work, enhancing productivity.
 - Clerical Workers: High AI exposure with low shielding—higher displacement risk.

Conceptual Diagram of AI Exposure (AIOE) and Complementarity (θ)

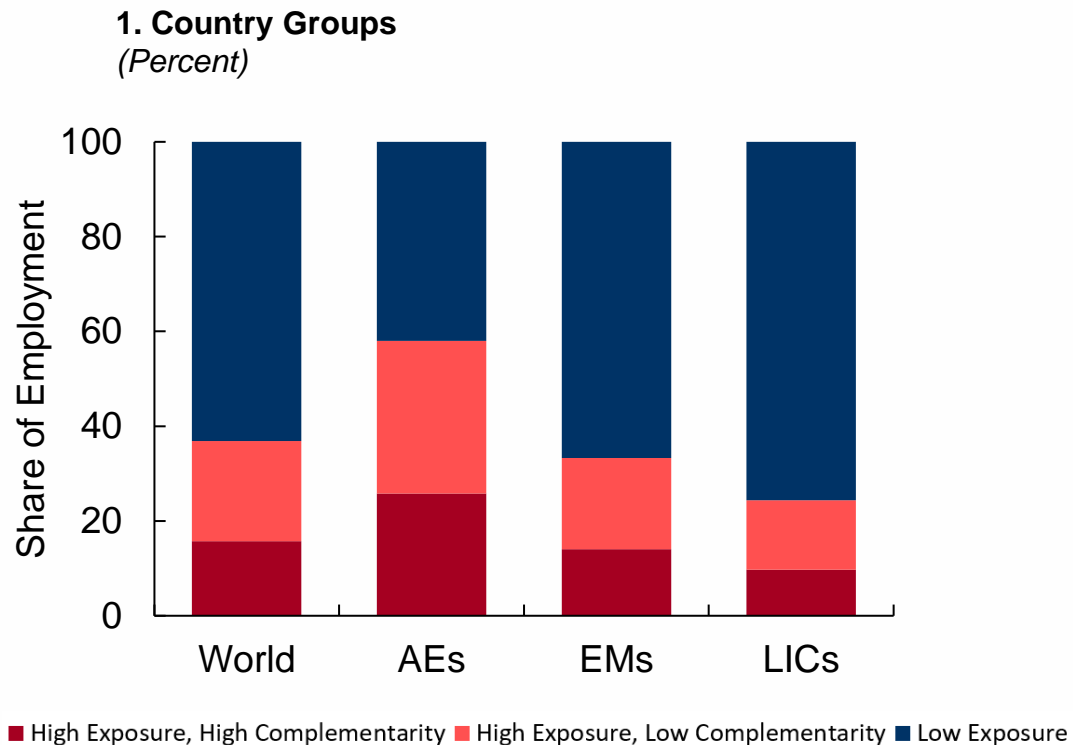


Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); and IMF staff calculations.

Note: Red reference lines denote the median of AIOE and complementarity.

About forty percent of workers worldwide and sixty percent in AEs is in high-exposure occupations

Employment Shares by AI Exposure and Complementarity



Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); International Labour Organization (ILO); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.

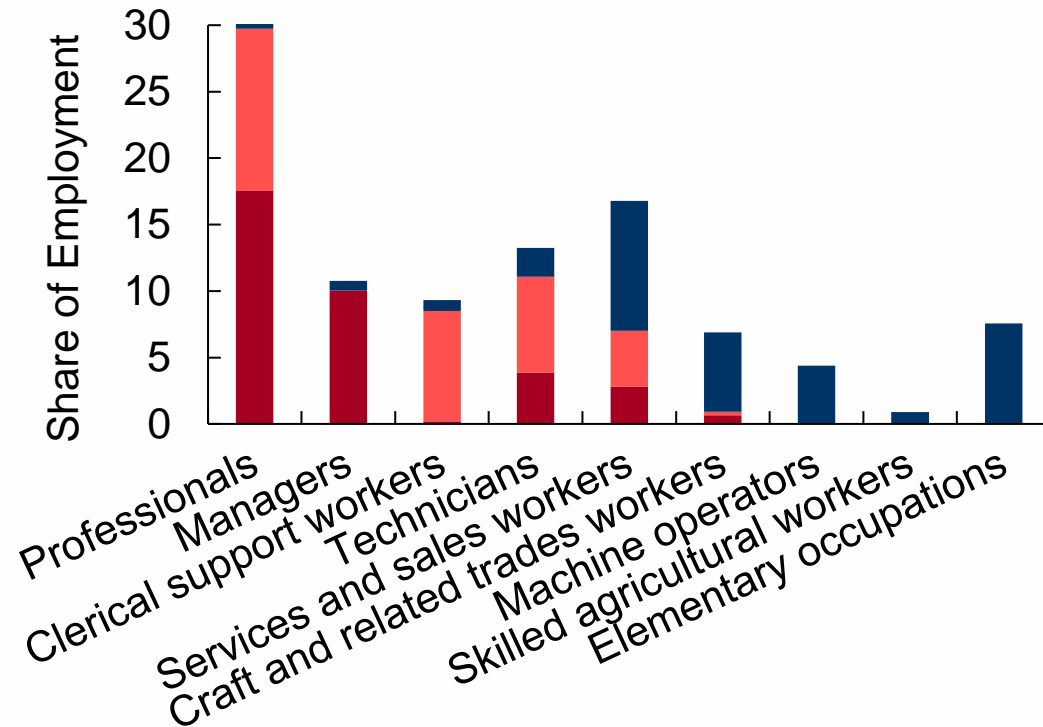
Note: Country labels use International Organization for Standardization (ISO) country codes. ISCO stands for International Standard Classification of Occupations. AEs = advanced economies; EMs = emerging markets; LICs = low-income countries; World = all countries in the sample. Share of employment within each country group is calculated as the working-age-population-weighted average.

- AI exposure and complementarity varies by income group:
 - AEs: 27% high-complementarity; 33% low complementarity jobs;
 - EMs: 16% high-complementarity; 24% low complementarity jobs;
 - LICs: 8% high-complementarity; 18% low complementarity jobs.
- AEs dominate in cognitive-intensive roles, potentially facing more immediate AI job disruption.
- However, AEs also have a stronger position to harness AI's growth potential.
- With appropriate digital infrastructure, AI could help EMDEs mitigate skill shortages.

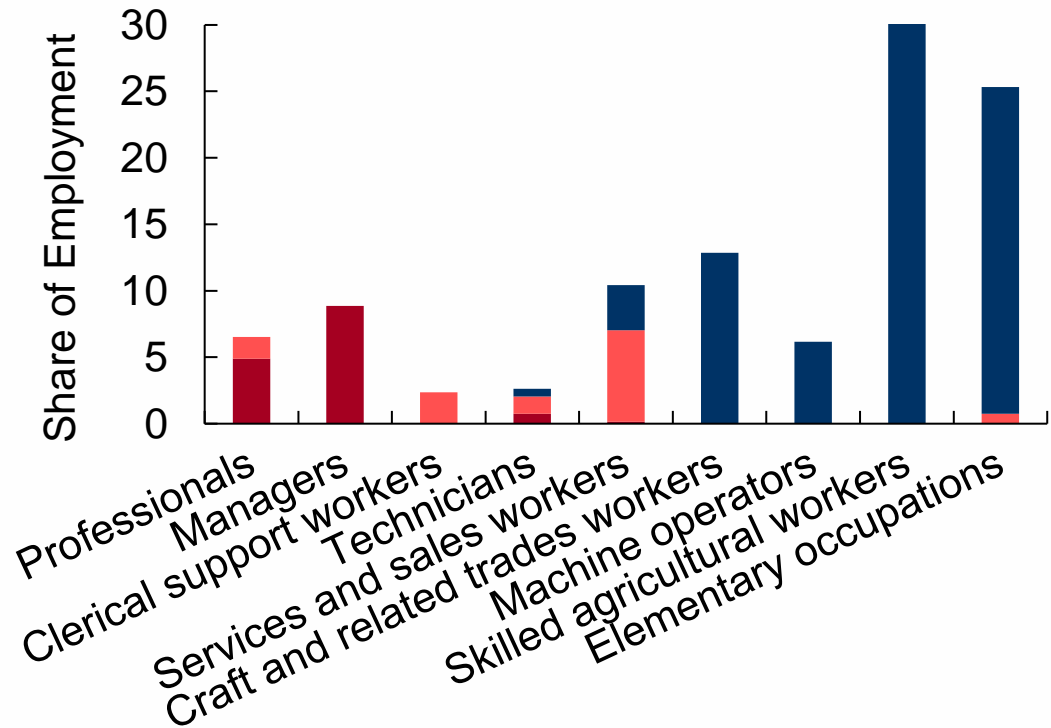
Labor force composition in terms of broad occupational groups largely explains the differences in exposure and complementarity across countries

Employment Share by Exposure and Complementarity

1. GBR
(Percent)



2. IND
(Percent)



■ High Exposure, High Complementarity ■ High Exposure, Low Complementarity ■ Low Exposure

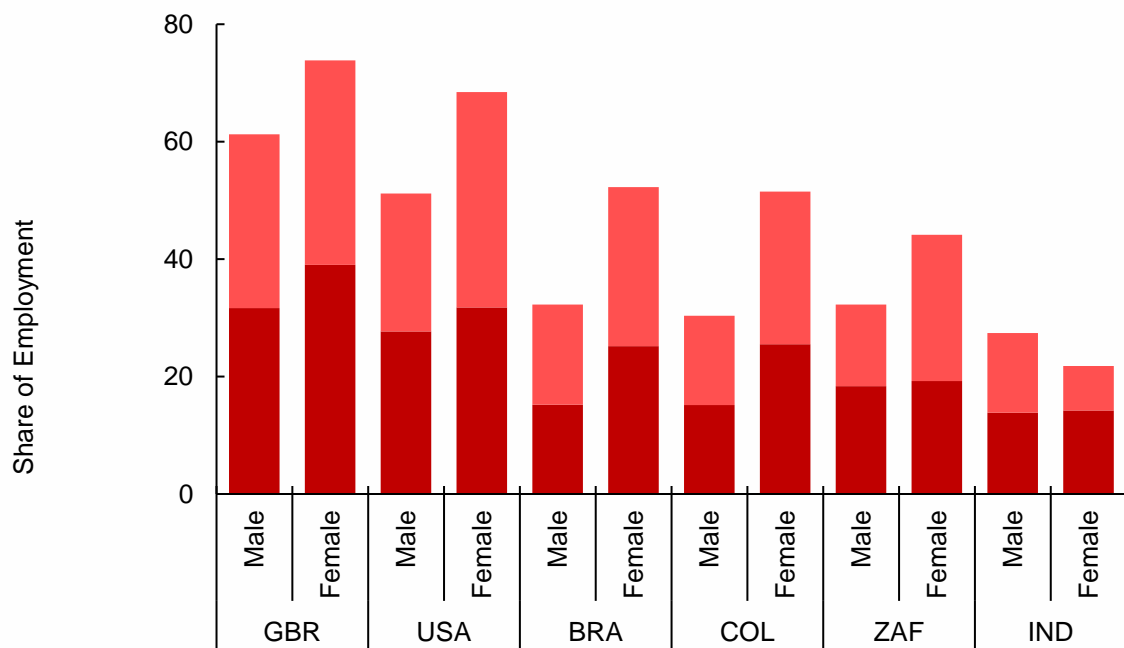
Sources: India Periodic Labour Force Survey (PLFS); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.

Note: The charts plot the total employment share by each of the nine 1-digit ISCO-08 occupation codes. Country names use International Organization for Standardization (ISO) country codes. ISCO stands for International Standard Classification of Occupations.

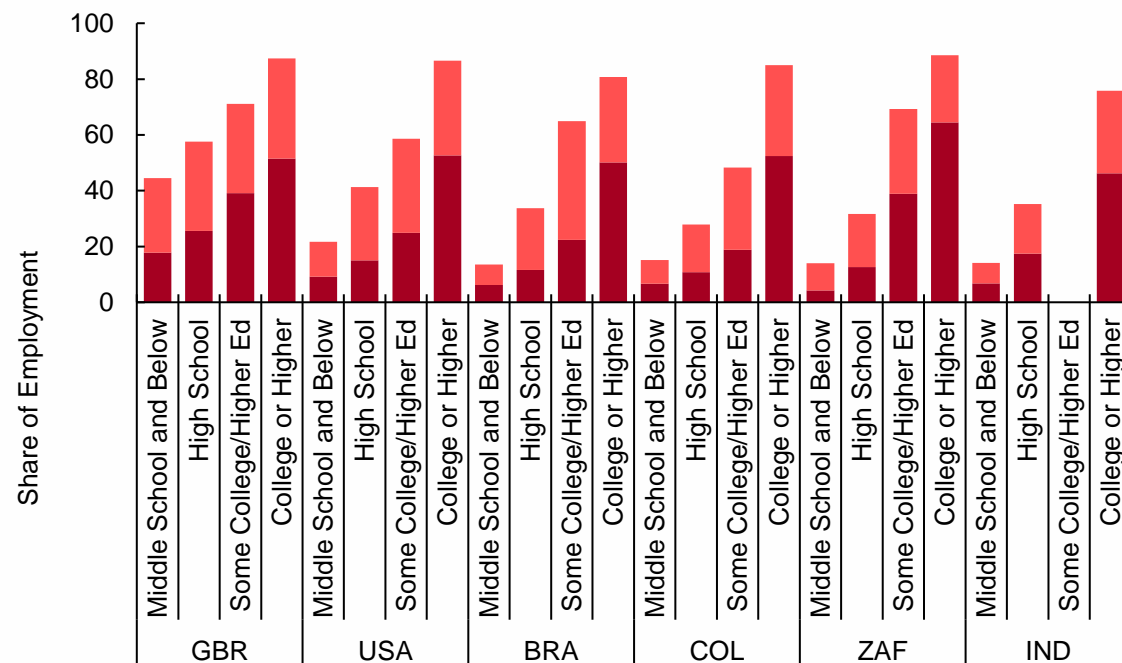
Exposure is higher for women and for more educated workers, but is mitigated by a higher potential for complementarity with AI

Share of Employment in High-Exposure Occupations by Demographic Groups

1. By Gender
(Percent)



2. By Education
(Percent)



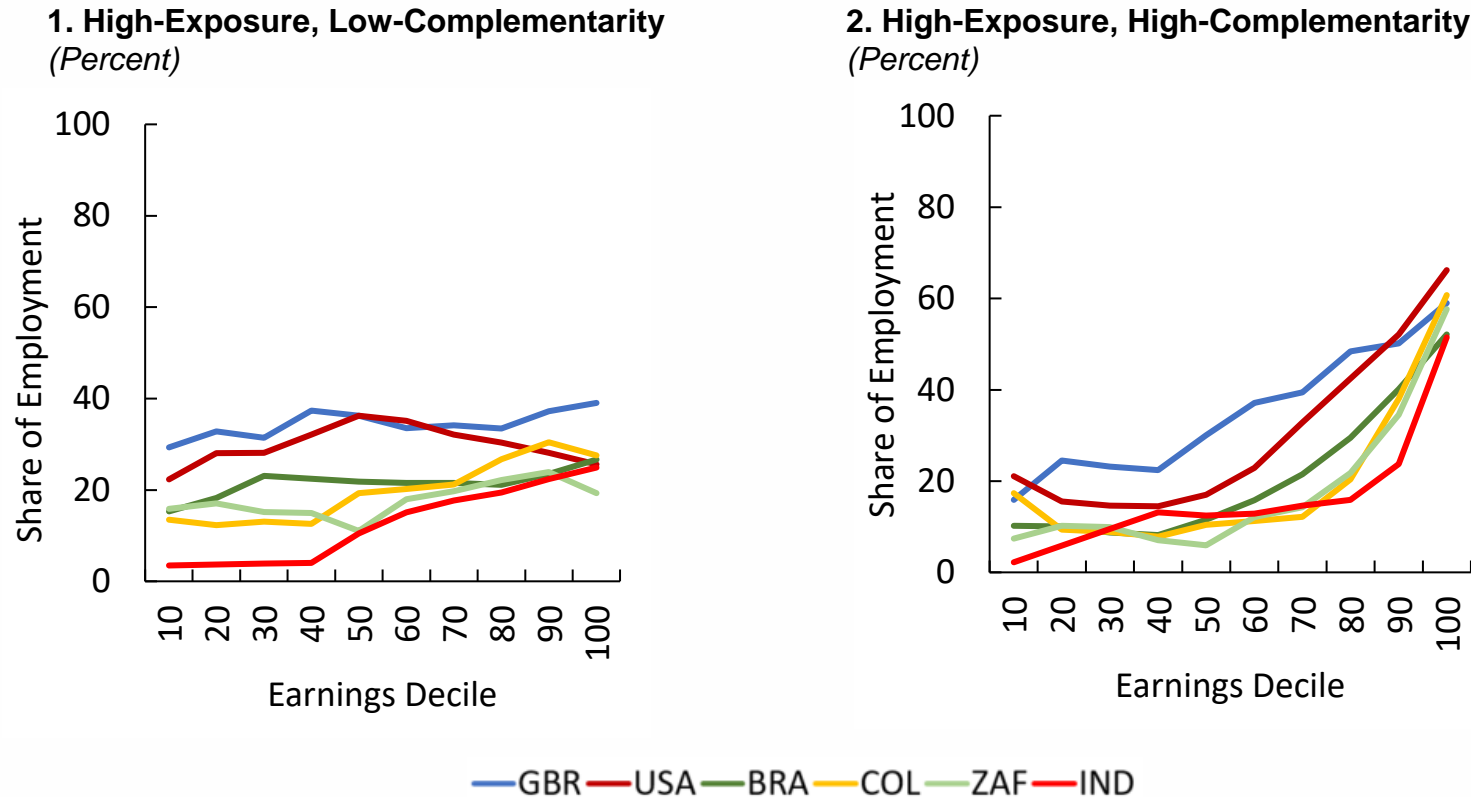
■ High Exposure, High Complementarity ■ High Exposure, Low Complementarity

Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.

Note: The bars in both plots represent employment shares in high-exposure occupations. In plot 1, employment shares are conditional on each gender category. In plot 2, employment shares are conditional on each of the four education categories (Middle School and Below, High School, Some College and College). In plot 3, employment shares are conditional on each of the four age intervals. Country labels use International Organization for Standardization (ISO) country codes.

Exposure is spread along the labor income distribution but potential gains from AI are positively correlated with income

Share of Employment in High-Exposure Occupations and Potential Complementarity by Income Deciles



Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); Pizzinelli and others (2023); UK Labour Force Survey (LFS); and IMF staff calculations.

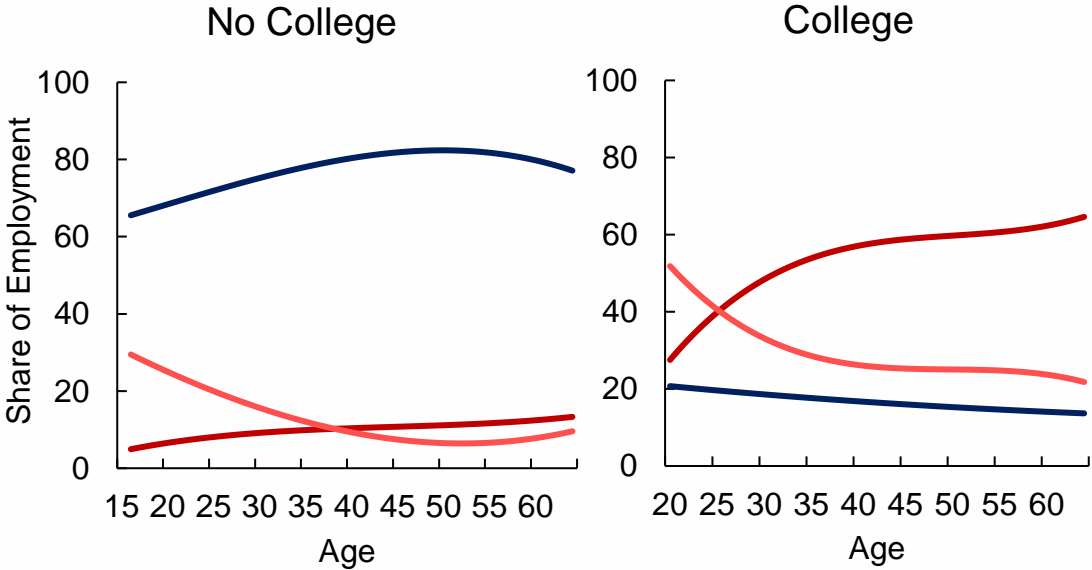
Note: Panel 1 shows the employment share in jobs with high exposure but low complementarity, and Panel 2 presents the employment share in jobs with high exposure and high complementarity, each categorized by income deciles. Panel 3 shows the potential AI occupational complementarity from Pizzinelli and others (2023), averaged and grouped by income deciles. Country labels use International Organization for Standardization (ISO) country codes.

Potential for Worker Reallocation in the AI-Induced Transformation: Evidence from Historical Transitions

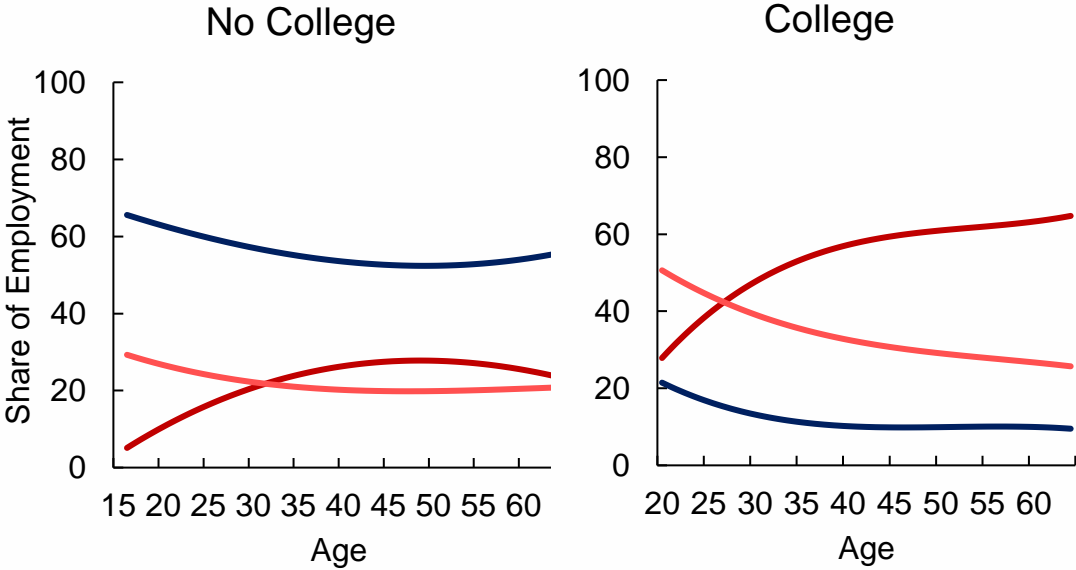
AI adoption both poses challenges and represents an opportunity for young college-educated workers' careers

Life Cycle Profiles of Employment Shares by Education Level

1. BRA
(Percent)



2. GBR
(Percent)



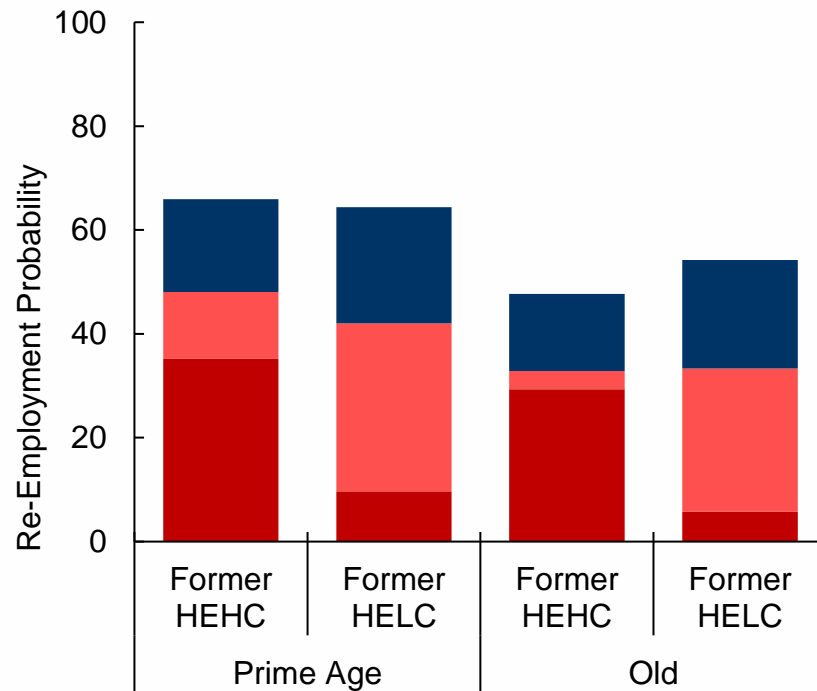
— High Exposure, High Complementarity — High Exposure, Low Complementarity — Low Exposure

Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
 Note: The figures plot the estimated share of employment by age for each exposure category for college and non-college educated workers, according to the calculations described in Annex 3. Country names use International Organization for Standardization (ISO) country codes.

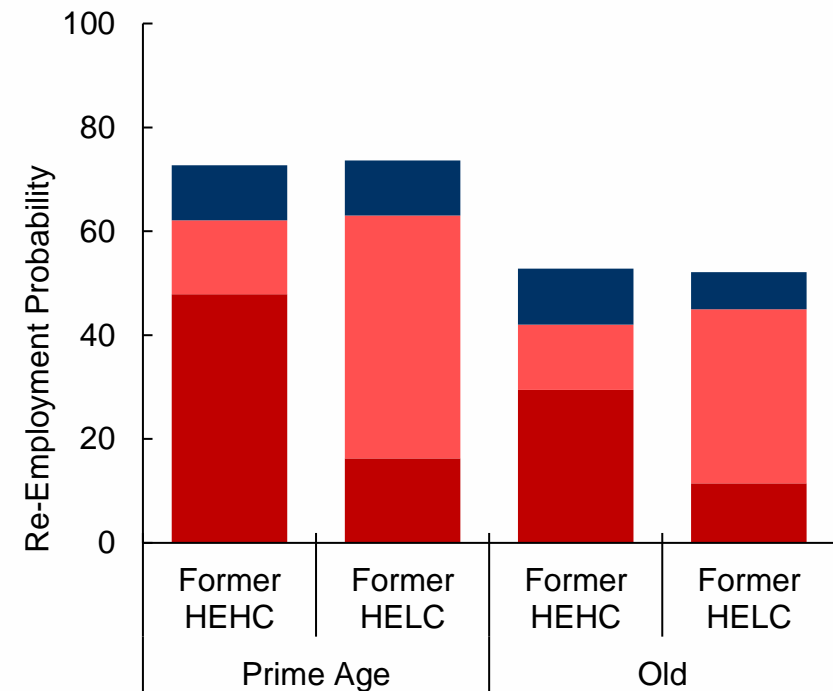
Older workers may be less adaptable and face additional barriers to mobility, as reflected in their lower likelihood to be re-employed after termination

1-Year Re-Employment Probability of Separated Workers

1. BRA



2. GBR



■ to High Exposure, High Complementarity (HEHC) ■ to High Exposure, Low Complementarity (HEL) ■ to Low Exposure (LE)

Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.

Note: The bars report the re-employment probability of workers who have recently (within the last quarter) transitioned from employment to unemployment, which is defined as the share of these workers who are again employed one year later. "From" indicates the exposure category of the occupation the individual had before being unemployed, while "to" indicates the exposure category of the occupation the worker transitioned to. "Prime Age" refers to workers over 35 and under 55, while "old" refers to workers 55 and older. Country names use International Organization for Standardization (ISO) country codes.

AI, Productivity, and Inequality

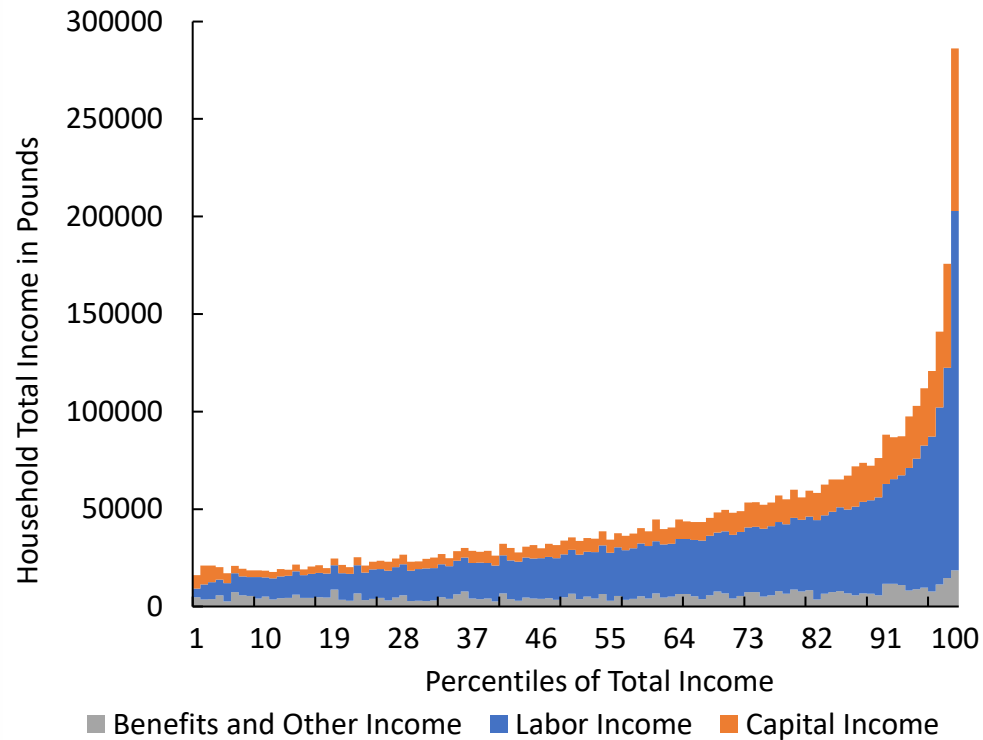
Model-based analysis of AI's economic impact

- **Task-based model** based on Moll et al. (2022) assesses effects on income distribution and wider economic impacts stemming from AI adoption.
- Model incorporates differences in labor productivity, asset holdings, AI exposure, and complementarity.
- **Four critical channels of impact of AI** are identified:
 1. **Labor displacement:** Shift of tasks from human labor to AI capital, reducing labor income.
 2. **Complementarity:** Value added shifts to AI-complementary occupations, increasing labor demand for these occupations and reducing it for others.
 3. **Productivity gains:** Overall economic boost potentially offsets labor income losses.
 4. **Capital income:** AI adoption leads to increases in the return of capital, raising capital income further.
- Calibration to the UK Economy; calibrate change in capital share to that from automation over 1980-2014
- Three scenarios: 1) Low complementarity; 2) higher complementarity; 3) higher complementarity and aggregate productivity

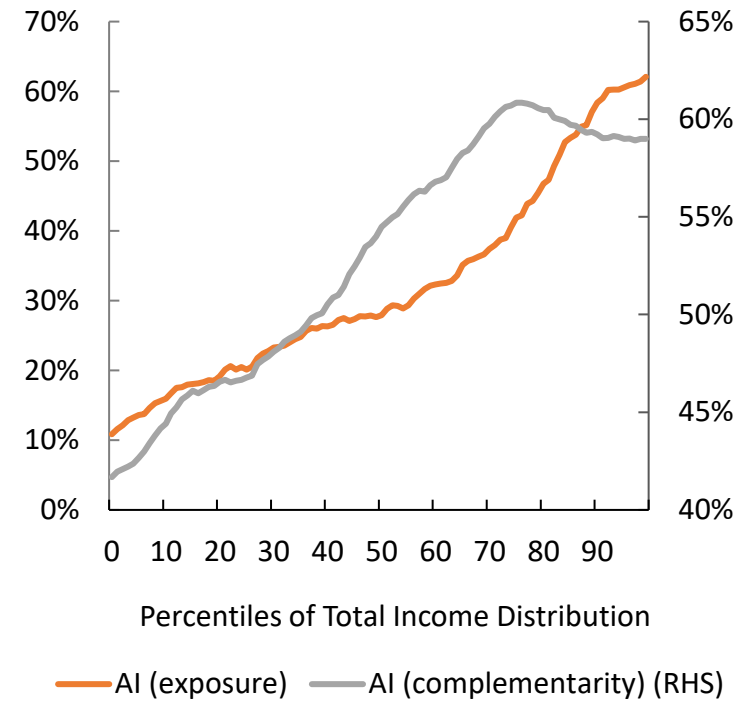
While middle and low-income workers' total income depends mostly on wage income, high-income workers have a large share of capital income.

Exposure to AI and Income in the UK

1. Exposure of Income to AI
(Pounds Sterling)



2. Exposure and Complementarity by Income Percentiles
(AI and Complementarity Index)



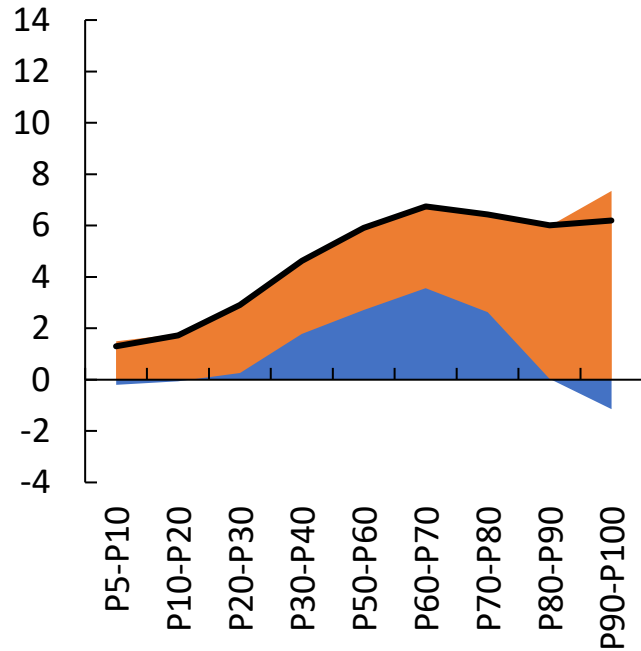
Sources: Wealth and Assets Survey (WAS); and IMF Staff calculations.

Note: Plot 1 reports three categories of workers' income by total income percentiles: (i) wage income, (ii) benefits, pensions, and other income, and (iii) capital income (rents and estimated investment income). In plot 2, AI exposure is measured as the share of total hours worked in a job in the top 30% of AI Occupational Exposure (AIOE) scores, from Felten, Raj, and Seamans (2021), weighted by hours worked. This threshold is chosen to make the analysis comparable to historical episodes of automation. AI complementarity is measured by considering the work contexts and skills, as discussed in Box 1 and in detail in Pizzinelli and others (2023). In the panel, we plot AI exposure and complementarity by total income percentiles.

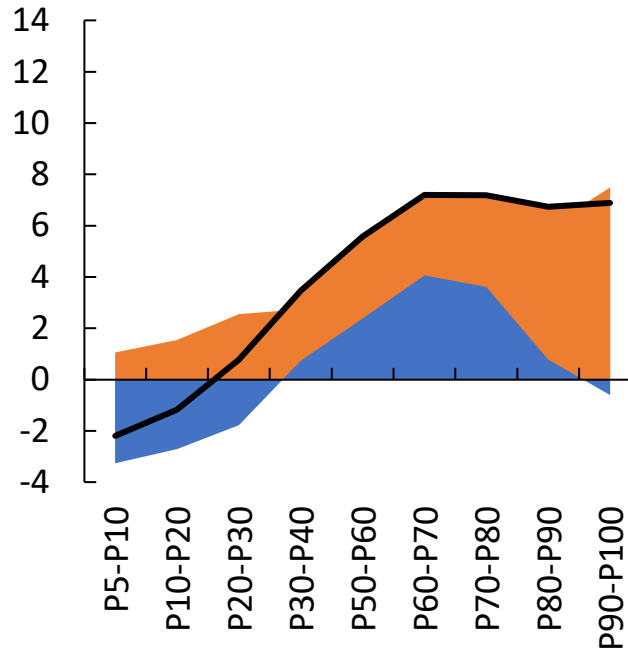
The impact of AI on labor income inequality depends on the degree of exposure to, and complementarity with, AI and its boost to productivity

Change in Total Income by Income Percentile Under Three Scenarios

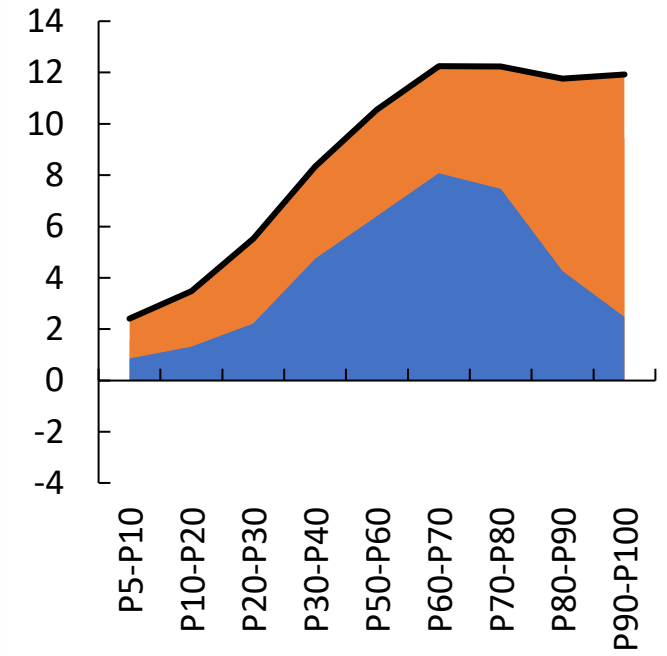
1. Low-Complementarity
(Percent)



2. High-Complementarity
(Percent)



3. High-Complementarity and High-Productivity
(Percent)



Capital income Labor income Total income

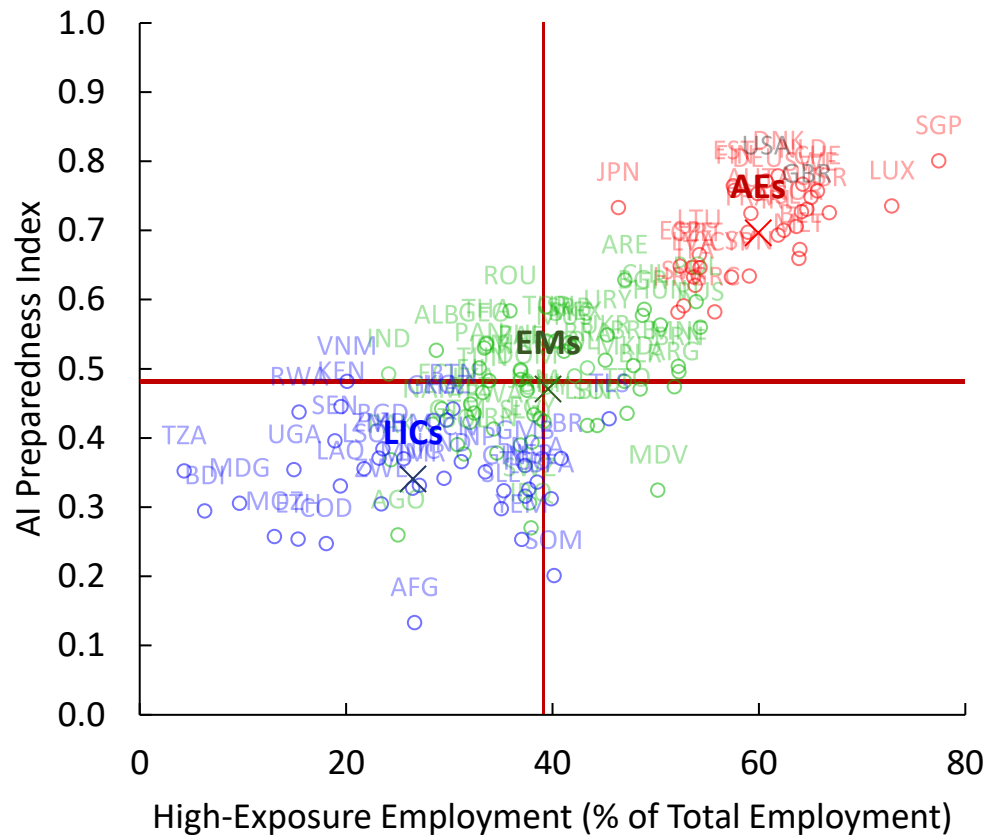
Sources: IMF staff calculations

Note: The plots represent three scenarios from the model: (i) low-complementarity, (ii) high-complementarity, and (iii) high-complementarity and high productivity. For all scenarios, the calibrated change in the capital share is the same: 5.5pp, based on the change in the capital share from 1980-2014. The plots show the change in total income by income percentile, decomposed into the change in labor income in blue and the change in capital income in red. For more details on the model see SDN Annex 4.

AI Preparedness

Higher-income economies, including AEs and some EMs, are generally better prepared than LICs to adopt AI

AI Preparedness Index and Employment Share in High-Exposure Occupations



- **AI Preparedness Index (APII)** measures readiness across multiple strategic AI adoption areas.
- Builds on cross-country technology diffusion and adoption research (Keller, 2004; Nicoletti et al., 2020).
- Index includes macro-structural indicators under **four themes**:

Foundational preparedness

1. **Digital infrastructure:** basis for AI tech diffusion and application.
2. **Human capital and labor market policies:** digital skill distribution and policies for labor transitions.

Second-generation preparedness

3. **Innovation and economic integration:** promotes R&D and global trade, attracting investments.
4. **Regulation and ethics:** legal framework's adaptability and governance for enforcement.

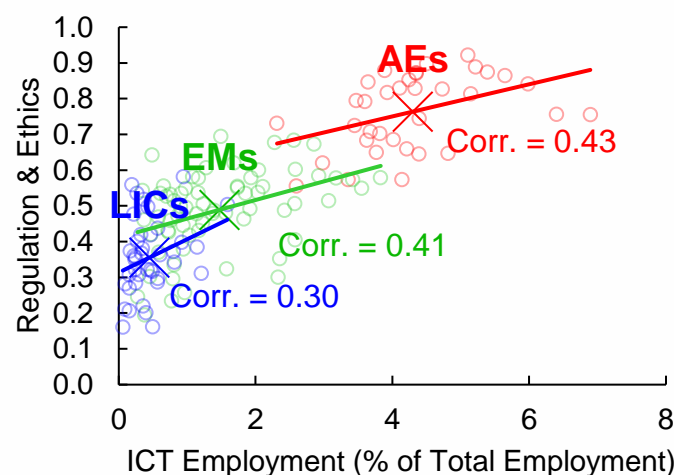
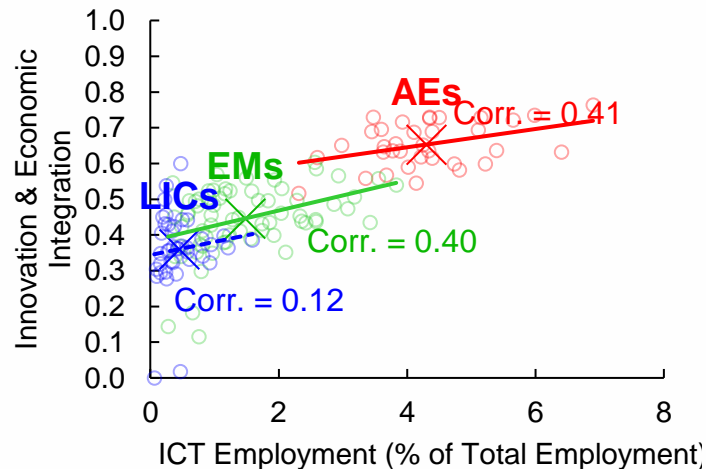
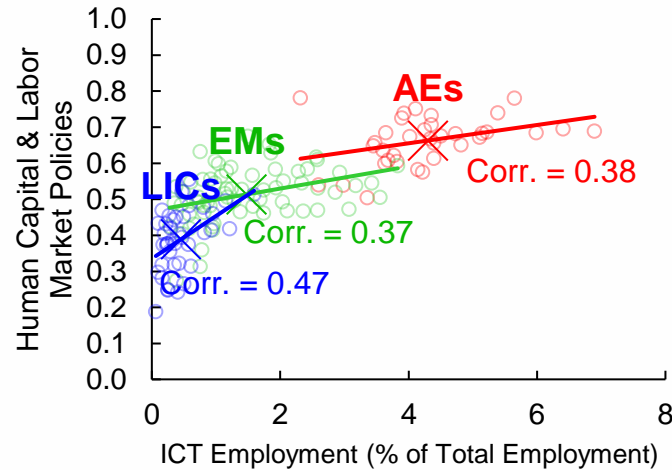
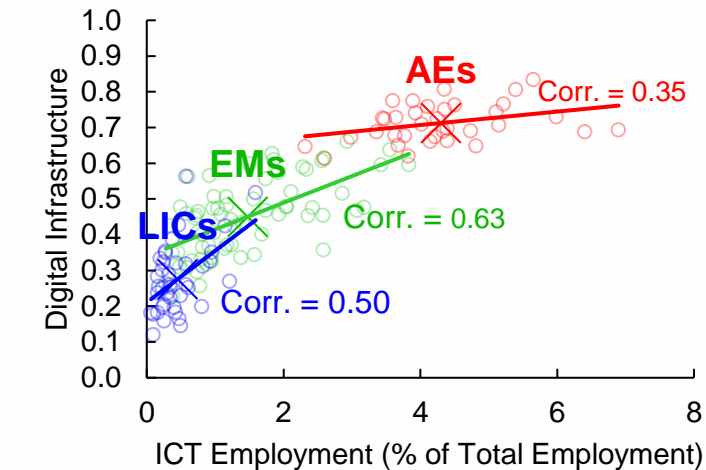
Sources: International Labour Organization (ILO); and IMF staff calculations.

Note: The plot includes 125 countries: 32 AEs, 56 EMs, and 37 LICs. The red reference lines are derived from the median values of the AI preparedness index and high-exposure employment. Circles represent the average values for each respective country group.

Crosses denote the average values for each corresponding country group AEs = advanced economies; EMs = emerging markets; LICs = low-income countries. Country labels use International Organization for Standardization (ISO) country codes.

Reform prioritization should align with AI preparedness gaps, which vary across the development spectrum

ICT Employment Share and Individual Components of the AI Preparedness Index



Policy prioritization should distinguish between:

- **Foundational AI preparedness** (digital infrastructure and human capital that enable workers and firms for AI adoption) is crucial for LICs and many EMs.
- **Second-generation preparedness** (innovation and legal frameworks) is crucial for AEs (and some EMs) with already strong foundational preparedness and digital skills.

Sources: International Labour Organization (ILO); and IMF staff calculations.

Note: ICT employment refers to people working in the information and communication sector based on ISIC-Rev 4 classification. 142 countries are included: 35 AEs, 67 EMs, and 40 LICs. Circles represent the average values for each respective country group. Crosses denote the average values for each corresponding country group. Simple correlation ("Corr.") is also added for each country group. Linearly fitted dash lines indicate statistical insignificance. AEs = advanced economies; EMs = emerging markets; LICs = low-income countries; ISIC = International Standard Industrial Classification.

Conclusions

Conclusions

- Almost 40% percent of global employment is exposed to AI.
 - ✓ 60% of AE jobs are exposed to AI, mostly cognitive roles.
 - ✓ AI exposure: 40% in EMs, 26% in LICs.
- AEs generally at greater risk but also better poised to exploit AI benefits than EMDEs.
- AI will impact income and wealth inequality.
- AI-induced productivity gains, if strong, could result in higher incomes for most workers.
- Young, college-educated workers are better prepared to transition from jobs at risk of displacement to high-complementarity jobs.
- Older workers may be more vulnerable to the AI-driven transformation.
- To harness AI's potential fully, priorities depend on countries' development levels.

Thank you!

INTERNATIONAL MONETARY FUND

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Prepared by Mauro Cazzaniga, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma Rockall, and Marina M. Tavares

SDN/2024/001

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**2024
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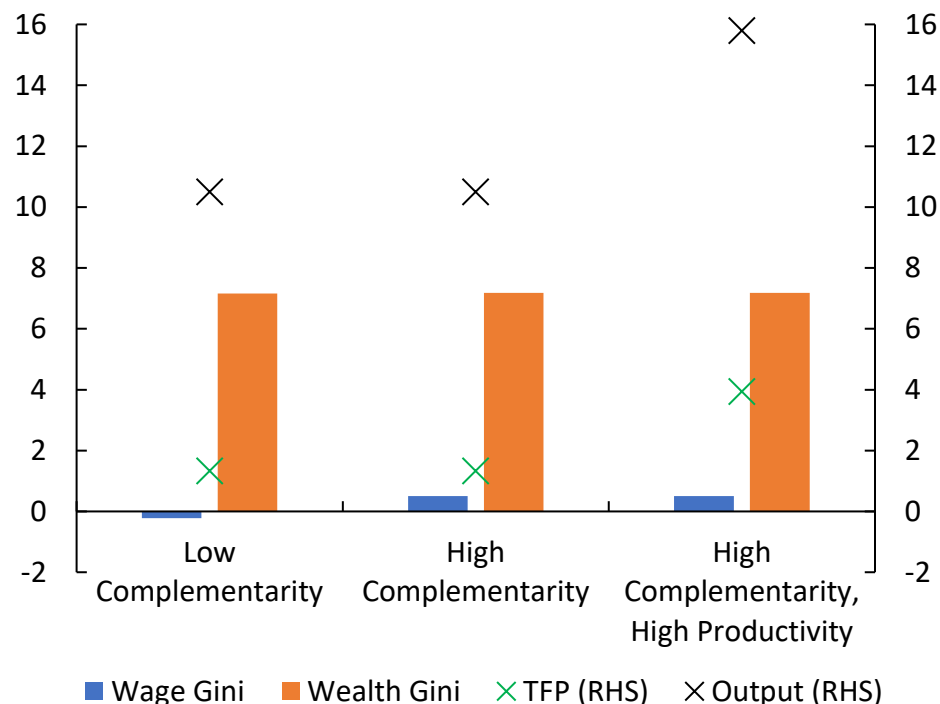
STAFF DISCUSSION NOTE

Additional Slides

Under the high-complementarity-high-productivity scenario, the increase in total national income is largest and benefits all workers, although gains are larger for those at the top.

Impact on Aggregates

(Percentage Point on LHS; Percent on RHS)



Sources: IMF Staff calculations.

Note: The figure shows the change in the aggregate wage and wealth Gini between the initial and final distribution in each scenario, as well as the change TFP and output. For more details on the model see SDN Annex 4. TFP = total factor productivity.

- **Scenario 1: Low AI Complementarity**
 - ▶ Output increases by nearly 10%
- **Scenario 2: High AI Complementarity**
 - ▶ Sectoral shift towards high-complementarity occupations.
 - ▶ Income increase is similar to first scenario; wage inequality rises.
- **Scenario 3: High Productivity Impact**
 - ▶ Output surges by 16%.
 - ▶ Income level rises for all workers

One important equation

- Aggregate Cobb-Douglas production function:

$$Y(K) := \mathcal{A}K^{\sum_z \alpha_z \eta_z} \prod_z (\psi_z \ell_z)^{(1-\alpha_z)\eta_z},$$

- η_z denotes the importance in value added of the tasks performed by skill z
- ψ_z denotes the productivity of labor for these tasks
- K denotes the aggregate stock of capital in the economy
- $1-\alpha_z$ is the labor share for skill z

Dimensions of AI Preparedness & Data Requirements

Dimension	Indicator
1. FOUNDATIONAL AI PREPAREDNESS	
I. Digital Infrastructure	
<i>Accessible, Affordable, and secured Internet Access</i>	<ul style="list-style-type: none"> - Estimated internet users per 100 inhabitants [UN] - Number of main fixed telephone lines per 100 inhabitants [UN] - Number of mobile subscribers per 100 inhabitants [UN] - Number of fixed broadband subscriptions per 100 inhabitants [UN] - Number of wireless broadband subscriptions per 100 inhabitants [UN] - Cost of internet access (percent of monthly GNI per capita) [ITU] - Secure Internet servers per 1 million people [WB]
<i>Mature e-commerce infrastructure</i>	<ul style="list-style-type: none"> - Private Sector's E-commerce Business Environment <ul style="list-style-type: none"> o Postal Reliability Index [UPU] o Use of mobile phone for online transactions (% of population ages 15+) [WB] - Public Sector's Online services Infrastructure [UN]
II. Human Capital and Labor Market Policies	
<i>Education and digital skills</i>	<ul style="list-style-type: none"> - Human Capital Index (i.e., mean years of schooling; expected years of schooling; gross enrolment ratio; adult literacy) [UN] - Public Education Expenditure (10-year average; %GDP) [WB] - Skillset of graduates (proxy for equality of education) [WEF] - Digital skills among active population (e.g., computer skills; basic coding, etc.) [UN] - Number of STEM graduates (10-year average; % of total graduates) [WB] - Number of female STEM graduates (10-year average; % of STEM graduates) [WB]
<i>Labor Market Flexibility & Policies</i>	<ul style="list-style-type: none"> - Flexibility of wage determination (centralized vs individual firm level) [WEF] - Social protection (% of population covered by social protection schemes) [ILO] - Internal labor market mobility [WEF] - Active labor market policies (e.g., skills matching, retraining) [WEF] - Pay and productivity (i.e., extent to which wages are market determined) [WEF]
2. SECOND-GENERATION AI PREPAREDNESS	
III. Innovation & Economic Integration	
<i>Innovation</i>	<ul style="list-style-type: none"> - R&D spending per unit of GDP [WB] - Frontier Technology Readiness (i.e., AI related R&D activity; number of scientific publications; number of patents on frontier technologies) [UN] - Domestic credit to private sector (%GDP) [WB]
<i>Economic Integration</i>	<ul style="list-style-type: none"> - Mean Tariff Rate [FI] - Non-tariff barriers [FI] - Free movement of capital and people (average of three indicators: financial openness; capital controls, and freedom of foreigners to visit) [FI]
IV. Regulation and Ethics	
<i>Strong legal frameworks and enforcement mechanisms</i>	<ul style="list-style-type: none"> - Legal framework's adaptability to digital business models [WEF] - Overall governance (proxy for enforcement/accountability) [WB]

Main Sources of Data for the AIPI Index

- International Labor Organization
- International Telecommunication Union
- United Nations
- Universal Postal Union
- World Bank
- World Economic Forum
- Fraser Institute