GEN-AI: ARTIFICIAL INTELLIGENCE AND THE FUTURE OF WORK

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Based on:
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.

Motivation and Focus

- Artificial Intelligence (AI) is set to profoundly change the global economy

- What are the implications for the future of work?

- The SDN 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

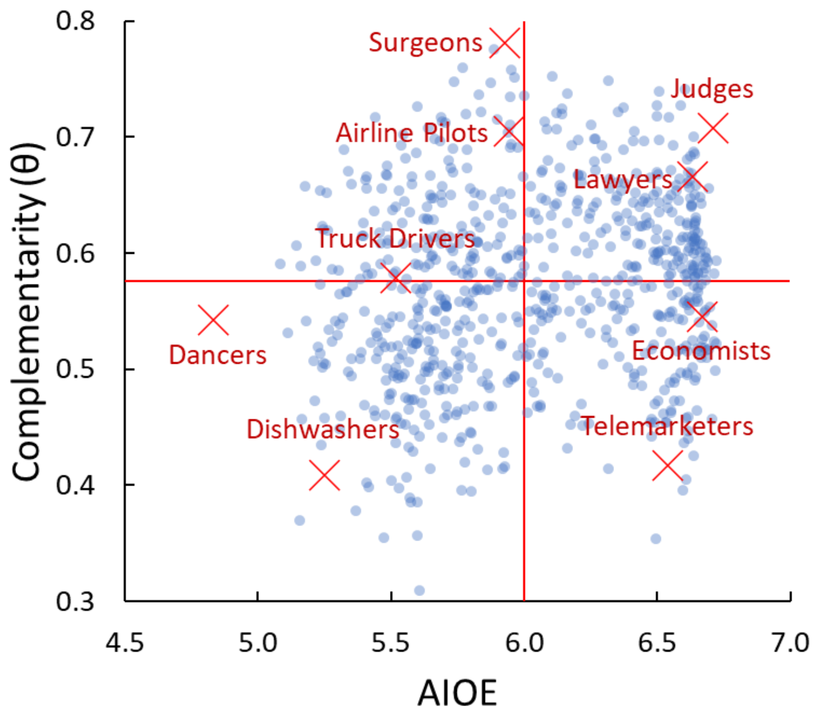
Measuring exposure to and complementarity with AI

- **Intuition: jobs are bundles of tasks**
  - Some tasks can be performed by AI (exposure to AI by Felten, Raj, and Seamans, 2021;2023).
  - BUT some tasks are shielded by social, ethical, physical context, and skill levels factors (Index developed by Pizzinelli et al., 2023)

- **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.

- **Complementarity potential:** Index developed by Pizzinelli et al. (2023):
  - Shielding factors: Social, ethical, physical context, and skill levels required by occupations.
  - Indicates occupations' protection from AI job displacement and identifies complementarity potential.
  - High complementarity potential derives from a combination of high AI exposure and high shielding.

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

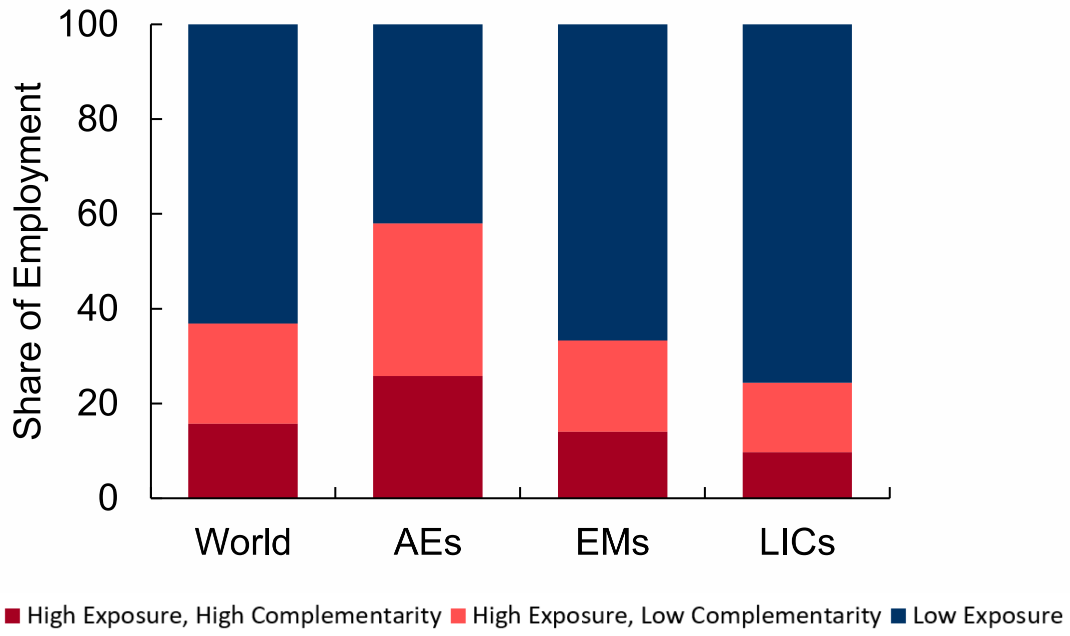


Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); and IMF staff calculations.
Note: Red reference lines denote the median of AIOE and complementarity.

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

Employment Shares by AI Exposure and Complementarity

1. **Country Groups**
(Percent)

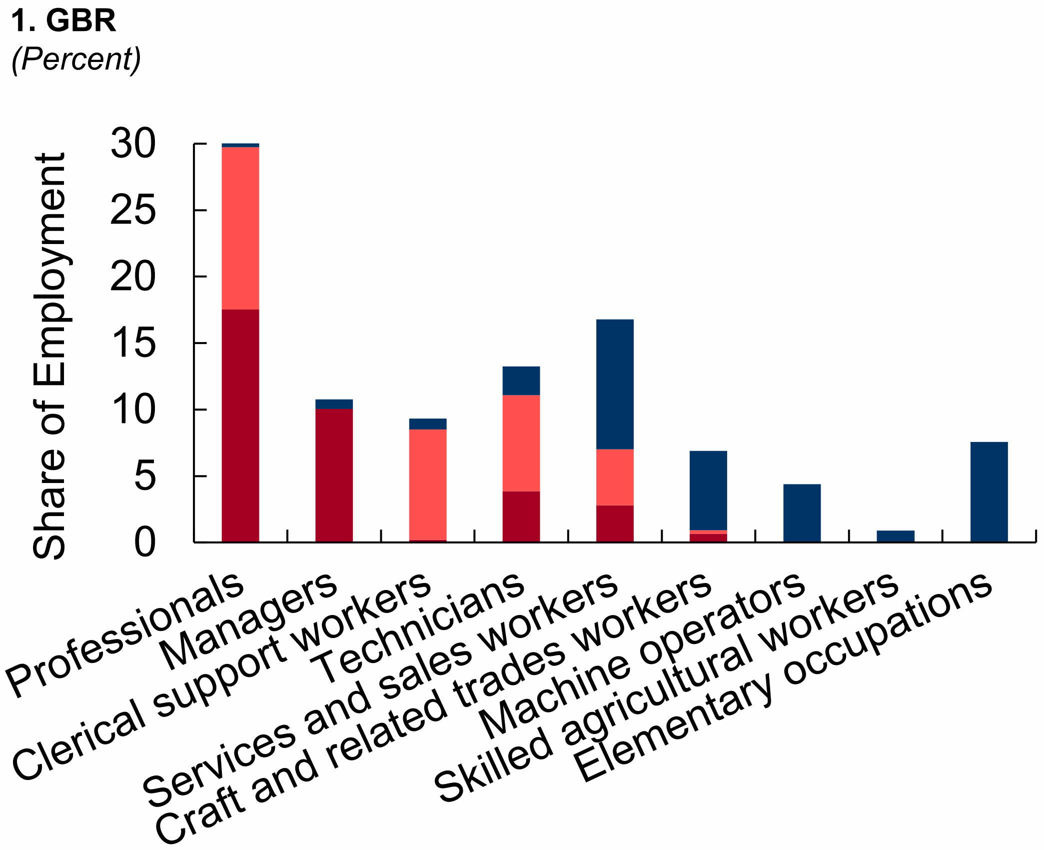


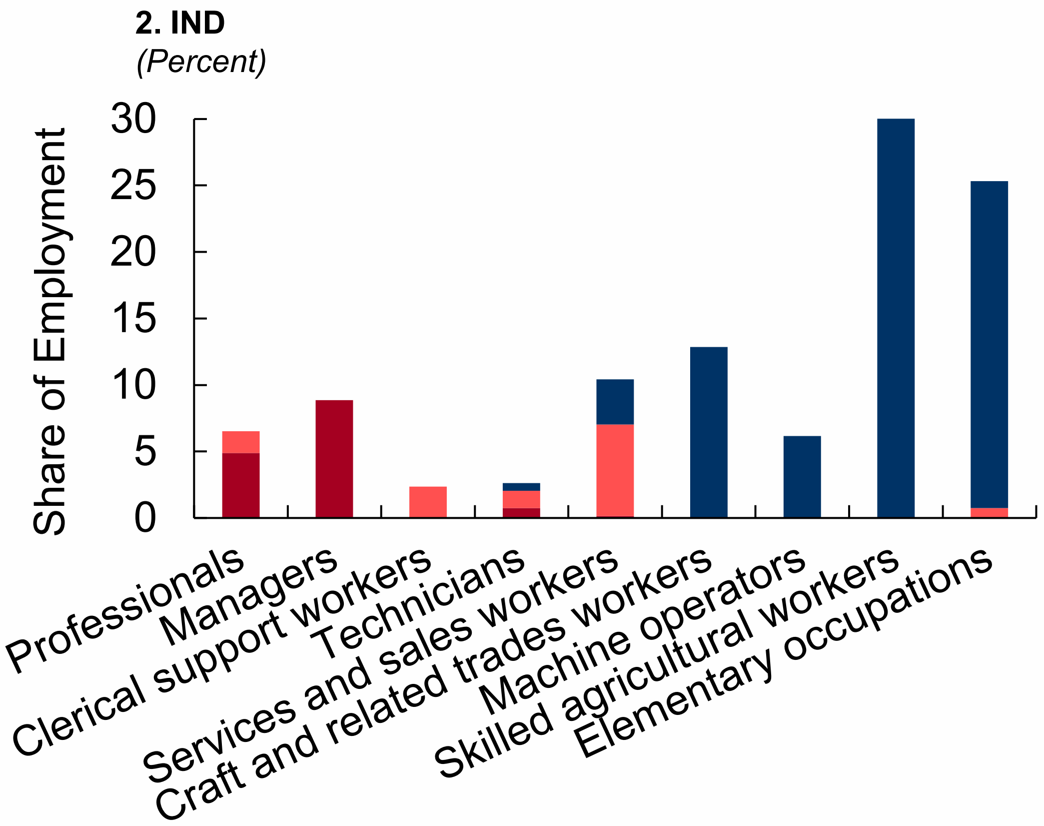
Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); International Labour Organization (ILO); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey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





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

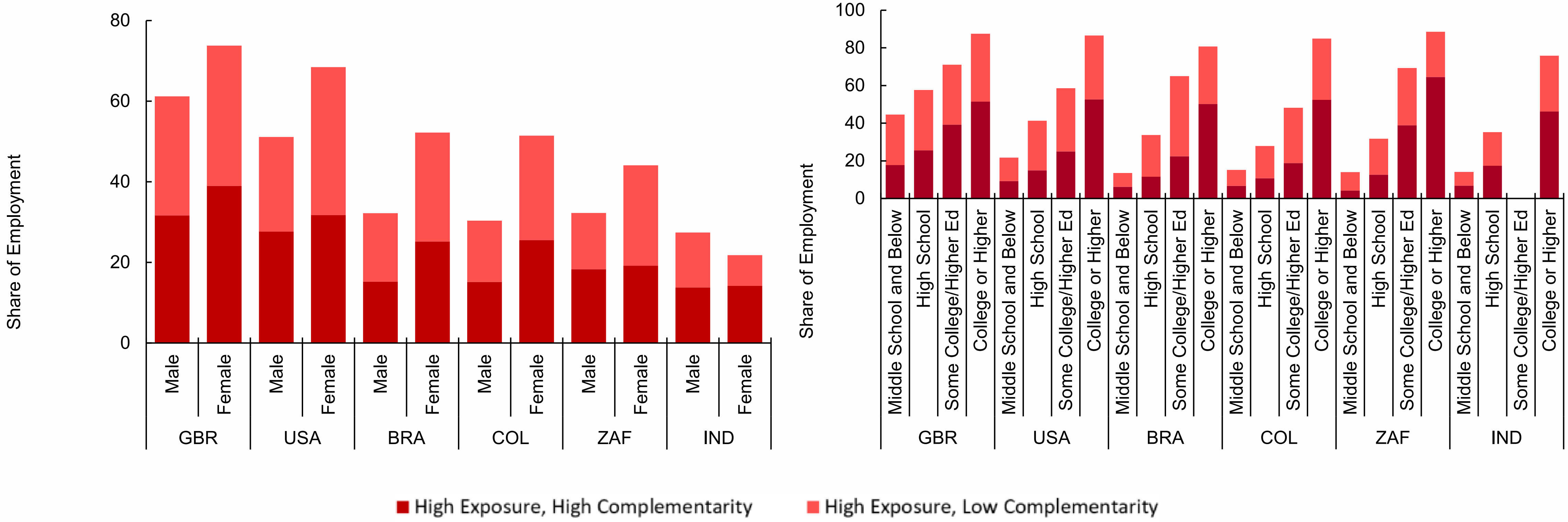
Sources: India Periodic Labour Force Survey (PLFS); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The charts plot the total employment share by each of the nine 1-digit ISCO-08 occupation codes. Country names use International 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)

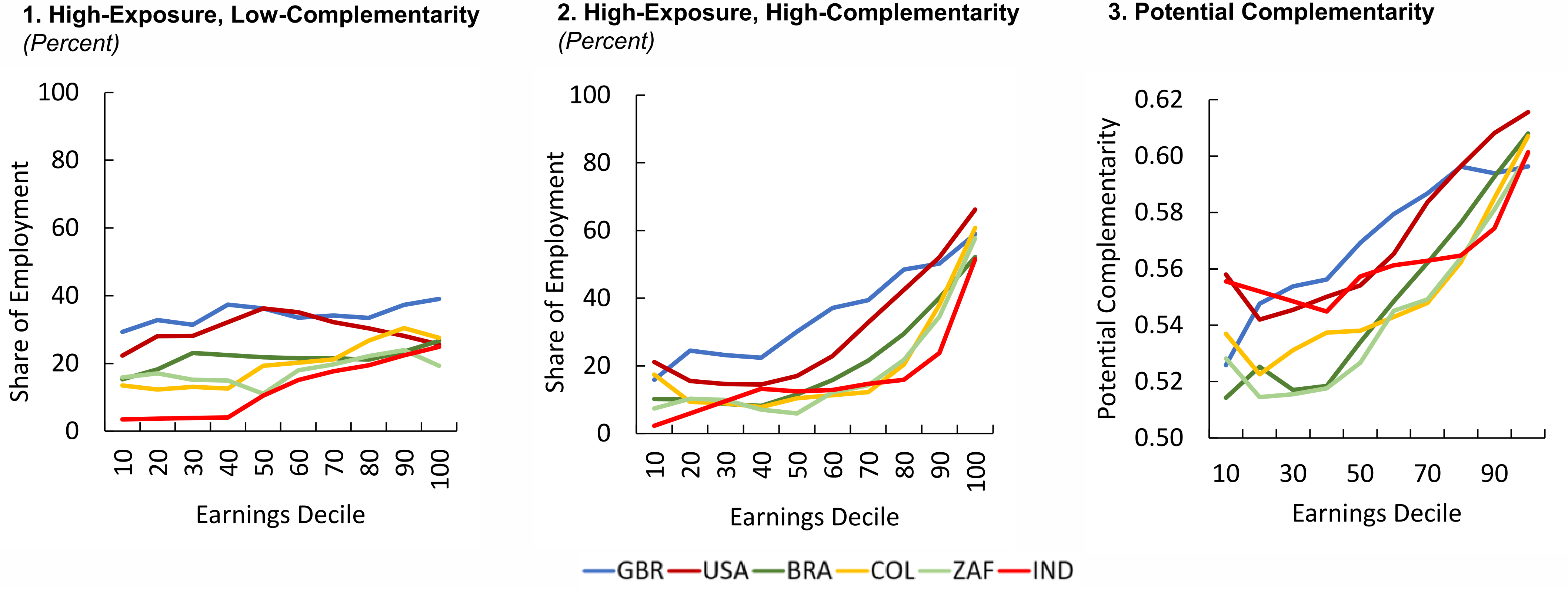
2. By Education
(Percent)



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.

AI, Productivity, and Inequality

Model-based analysis of AI's economic impact

- **Task-based model** by Rockall, Pizzinelli and Tavares (2023) 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.

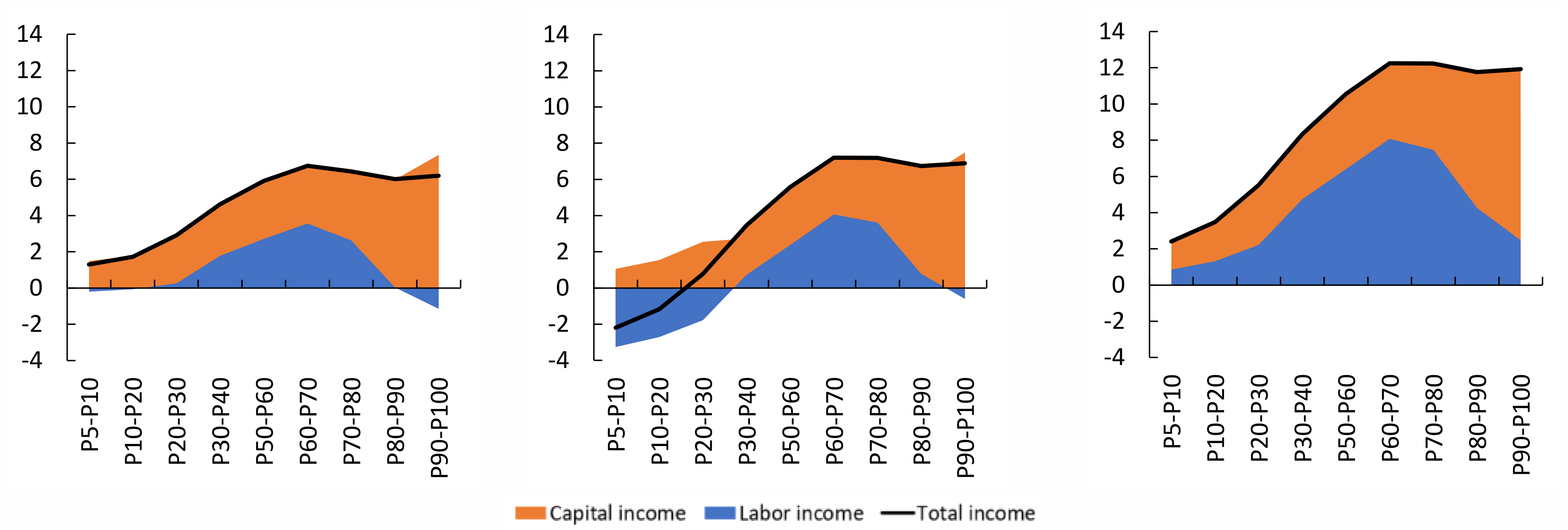
The impact of AI on labor income inequality depends on the degree of exposure to, and complementarity with, AI and its boost to productivity

Change in Total Income by Income Percentile Under Three Scenarios

1. Low-Complementarity
(Percent)

2. High-Complementarity
(Percent)

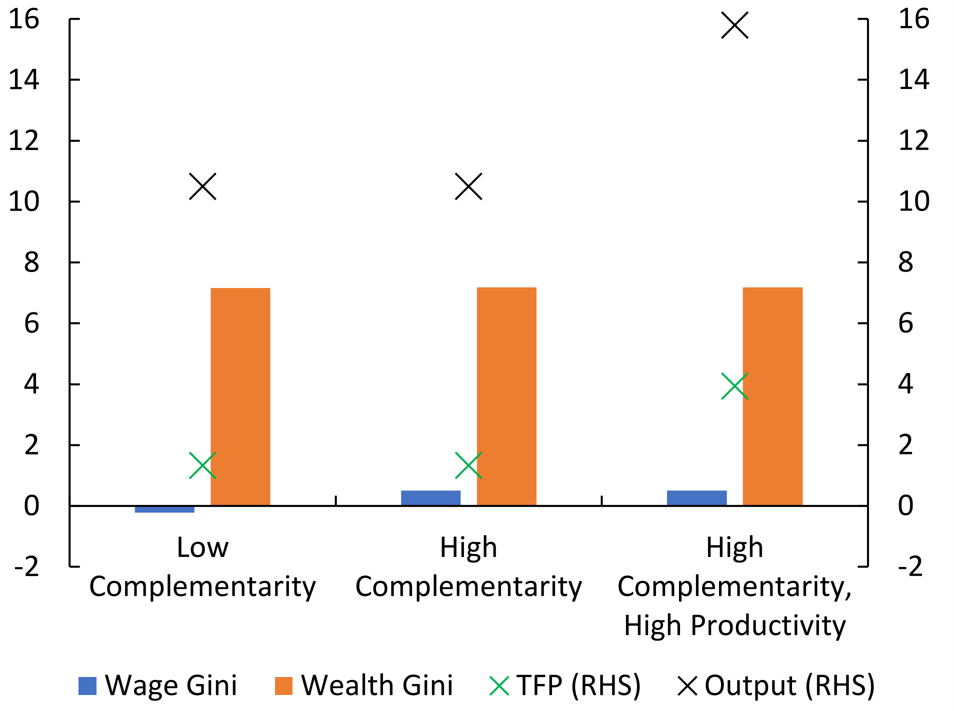
3. High-Complementarity and High-Productivity
(Percent)



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.

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.

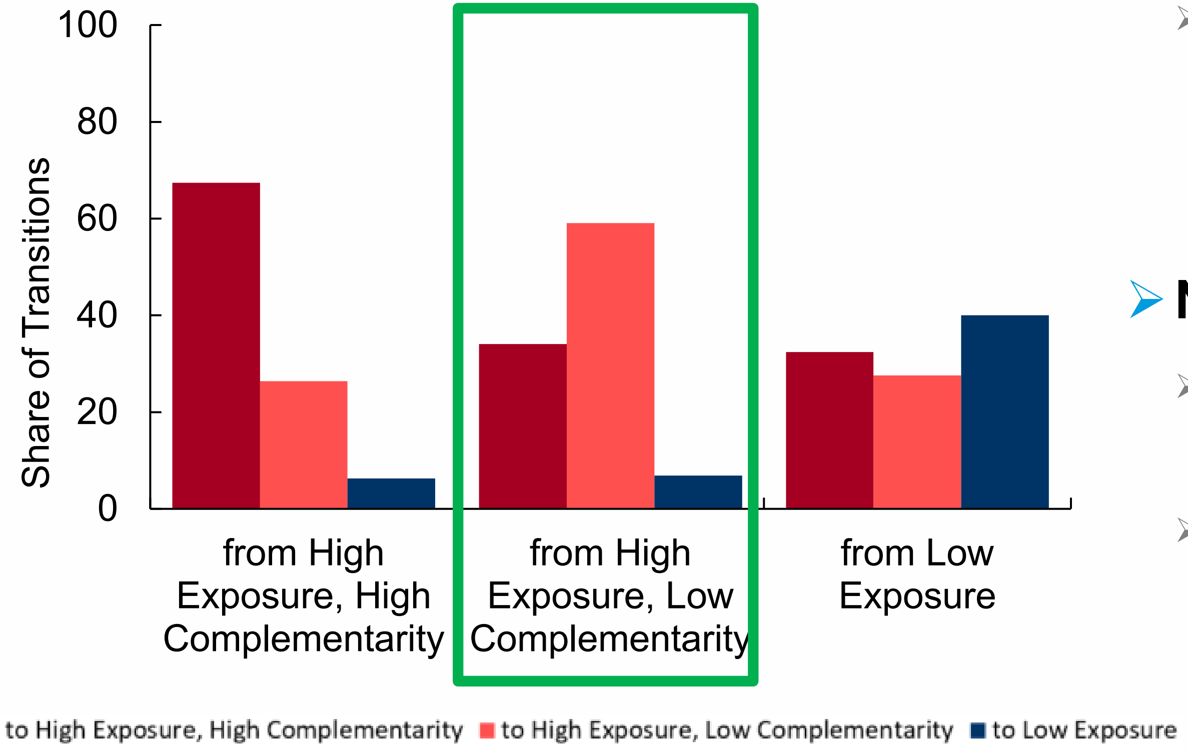
- **Scenario 1:** *Low AI Complementarity*
  - Output increases by nearly 10%
- **Scenario 2:** *High AI Complementarity*
  - Sectoral shift towards high-complementarity occupations.
  - Income increase is similar to first scenario; wage inequality rises.
- **Scenario 3***: High Productivity Impact*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

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

Workers with college education have historically shown a greater ability to transition into what are now jobs with high AI-complementarity potential

Occupational Transitions for College-Educated Workers

Example: GBR
(Percent)



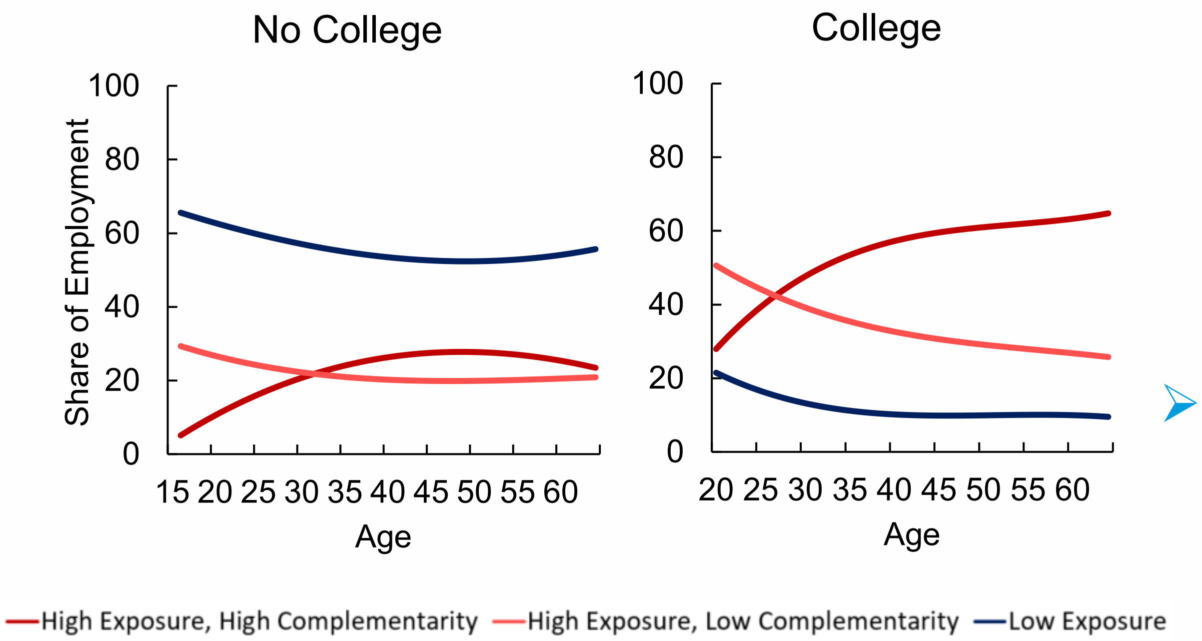
- Workers with a **college education:**
  - One third of those in “at risk” jobs are able to transition to jobs with high AI-complementarity potential
- **Non-college-educated** workers:
  - They are predominantly found in low-AI-exposure jobs
  - But are less inclined to move to high-complementarity positions when they switch from “at risk” jobs

Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: “From” indicates the exposure category of the occupation the individual had in the preceding quarter, while “to” indicates the exposure category of the occupation the worker transitioned to. The share of transitions represents the average share of transitions in the “from” category for college-educated workers that go to the “to” category. Country names use International Organization for Standardization (ISO) country codes.

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

Life Cycle Profiles of Employment Shares by Education Level

Example: GBR
(Percent)



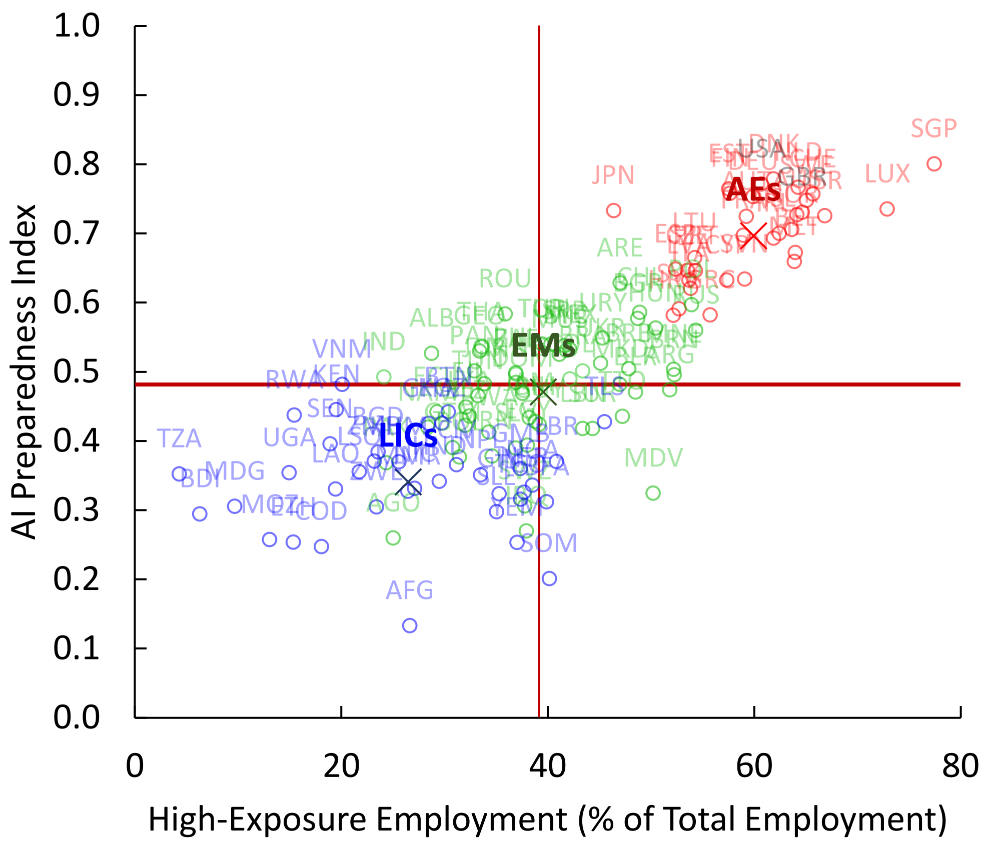
Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The figures plot the estimated share of employment by age for each exposure category for college and non-college educated workers, according to the calculations described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

- For **younger** workers
  - There is a risk of missing stepping-stone jobs which may make labor market entry more difficult
  - But AI may enable young college-educated workers to become experienced and productive more quickly (Brynjolfsson, Danielle, and Raymond 2023)
- For **older** workers:
  - They may be less adaptable and face additional barriers to mobility, as reflected in their lower likelihood of reemployment after termination.
  - They may have less incentives/less opportunities to learn new technologies

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

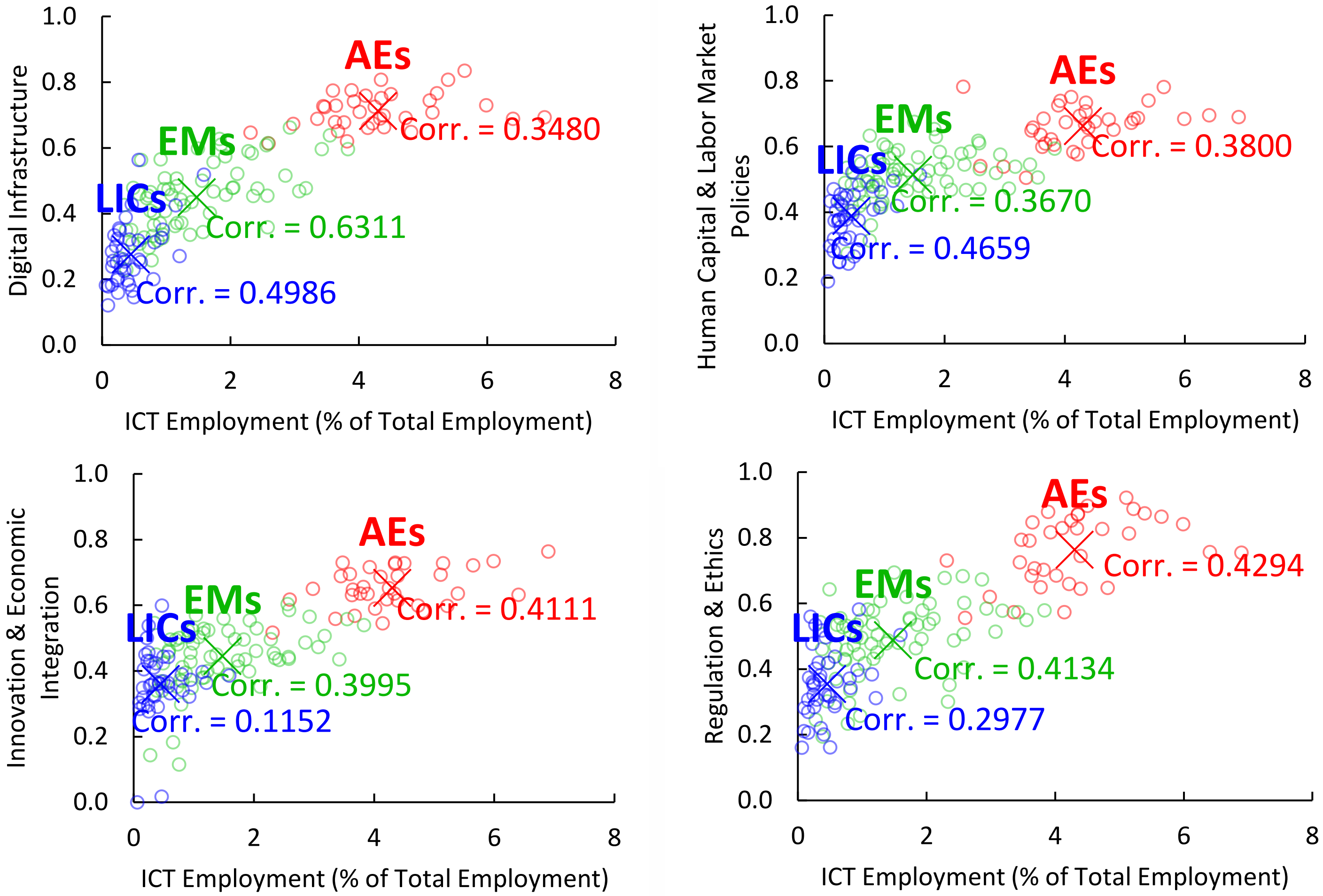


Sources: International Labour Organization (ILO); and IMF staff calculations.
Note: The plot includes 125 countries: 32 AEs, 56 EMs, and 37 LICs. The red reference lines are derived from the median values of the AI preparedness index and high-exposure employment. Circles represent the average values for each respective country group. Crosses denote the average values for each corresponding country group AEs = advanced economics; EMs = emerging markets; LICs = low-income countries. Country labels use International Organization for Standardization (ISO) country codes.

- **AI Preparedness Index (AIPI)** 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**:
  1. **Digital infrastructure:** basis for AI tech diffusion and application.
  2. **Innovation and economic integration:** promotes R&D and global trade, attracting investments.
  3. **Human capital and labor market policies:** digital skill distribution and policies for labor transitions.
  4. **Regulation and ethics:** legal framework's adaptability and governance for enforcement.

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



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. AEs = advanced economics; EMs = emerging markets; LICs = low-income countries; ISIC = International Standard Industrial Classification.

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.

Summary

- 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. But older workers may be more vulnerable to the AI-driven transformation.

- To harness AI's potential fully, priorities depend on countries' development levels.
  - ✓ AEs and some EMs ahead in AI readiness compared to LICs.
  - ✓ AEs and better prepared EMs should focus on AI regulation and invest in AI innovation and integration.
  - ✓ EMDEs need digital infrastructure and training.
  - ✓ For all economies, social safety nets and retraining for AI-susceptible workers are crucial to ensure inclusivity