GEN-AI: ARTIFICIAL INTELLIGENCE AND THE FUTURE OF WORK

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

International Monetary Fund – Research Department

Focus

- Artificial Intelligence (AI) is set to profoundly change the global economy
- What are the implications for the future of work, macroeconomy and income distribution?
- Focus:
  - 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

Measuring exposure to and complementarity with AI

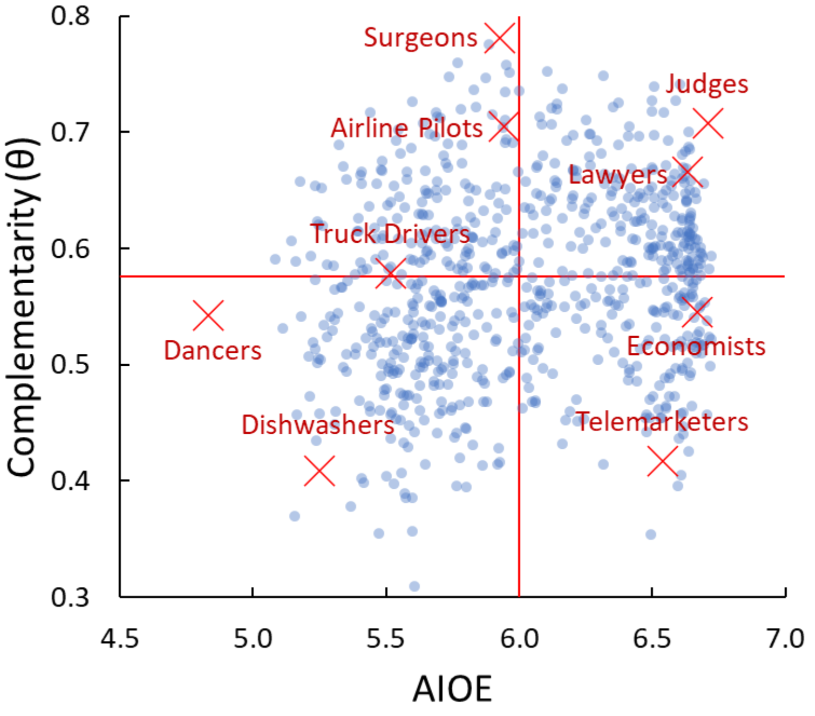
- **Exposure to AI:** Degree of overlap between AI applications and human abilities in occupations (Felten et al., 2021;2023).

- **Complementarity (or Shielding) Index:** Leverage 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)

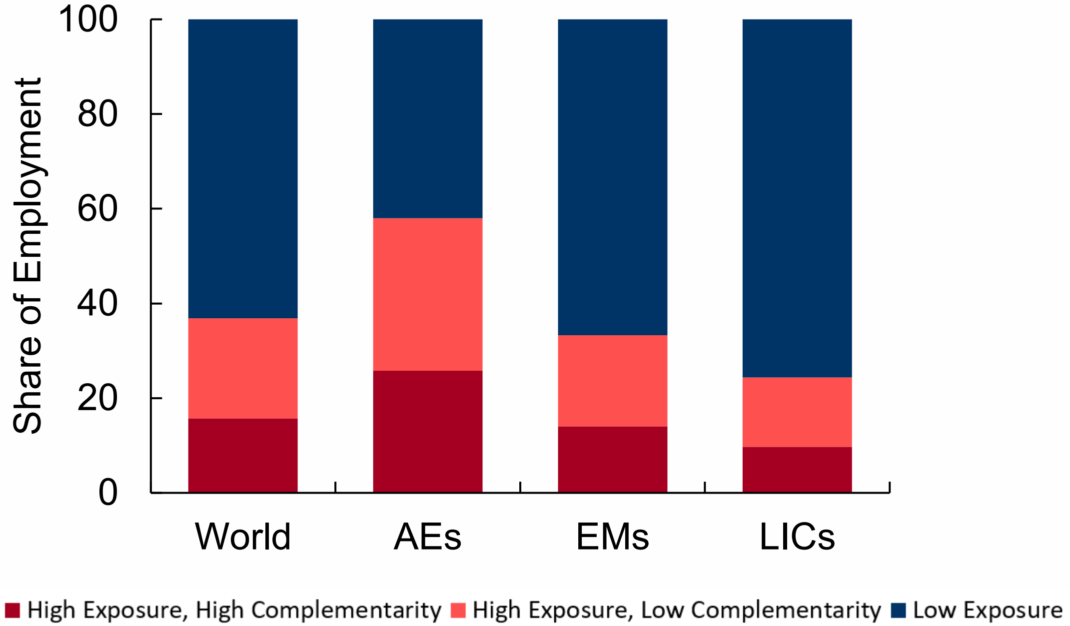


Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); and IMF staff calculations.
Note: Red reference lines denote the median of AIOE and complementarity.

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

Employment Shares by AI Exposure and Complementarity

1. Country Groups
(Percent)

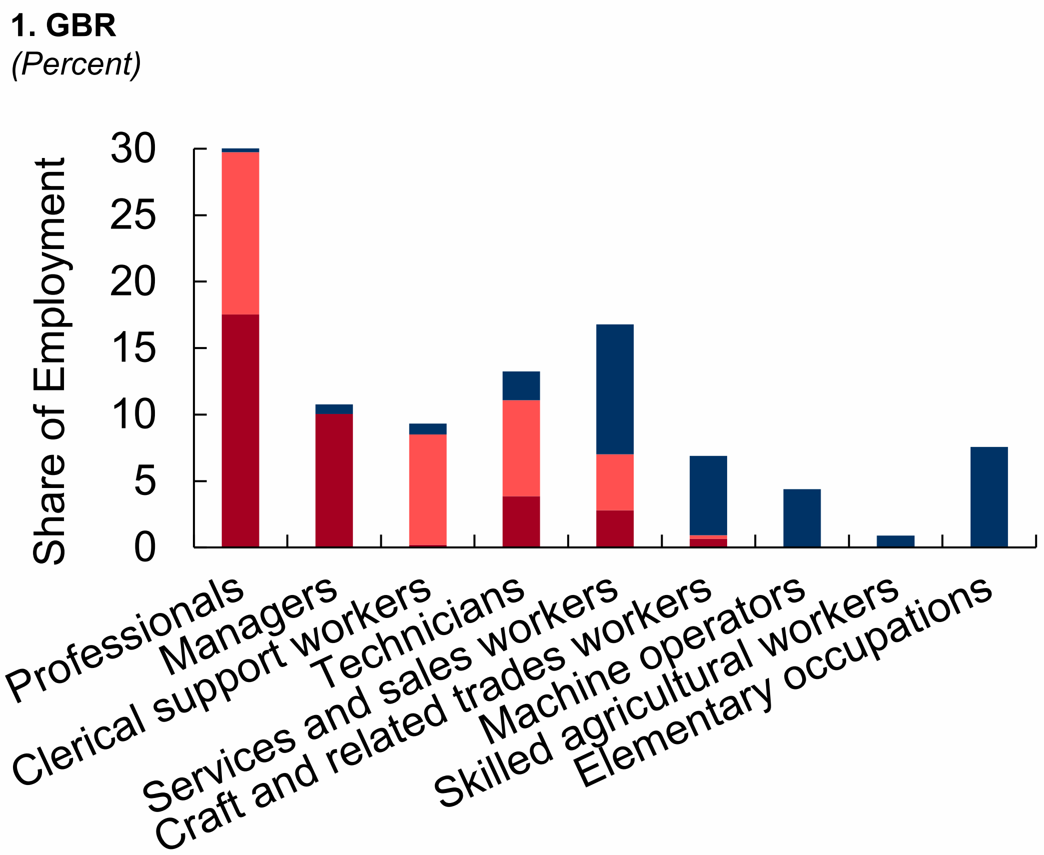


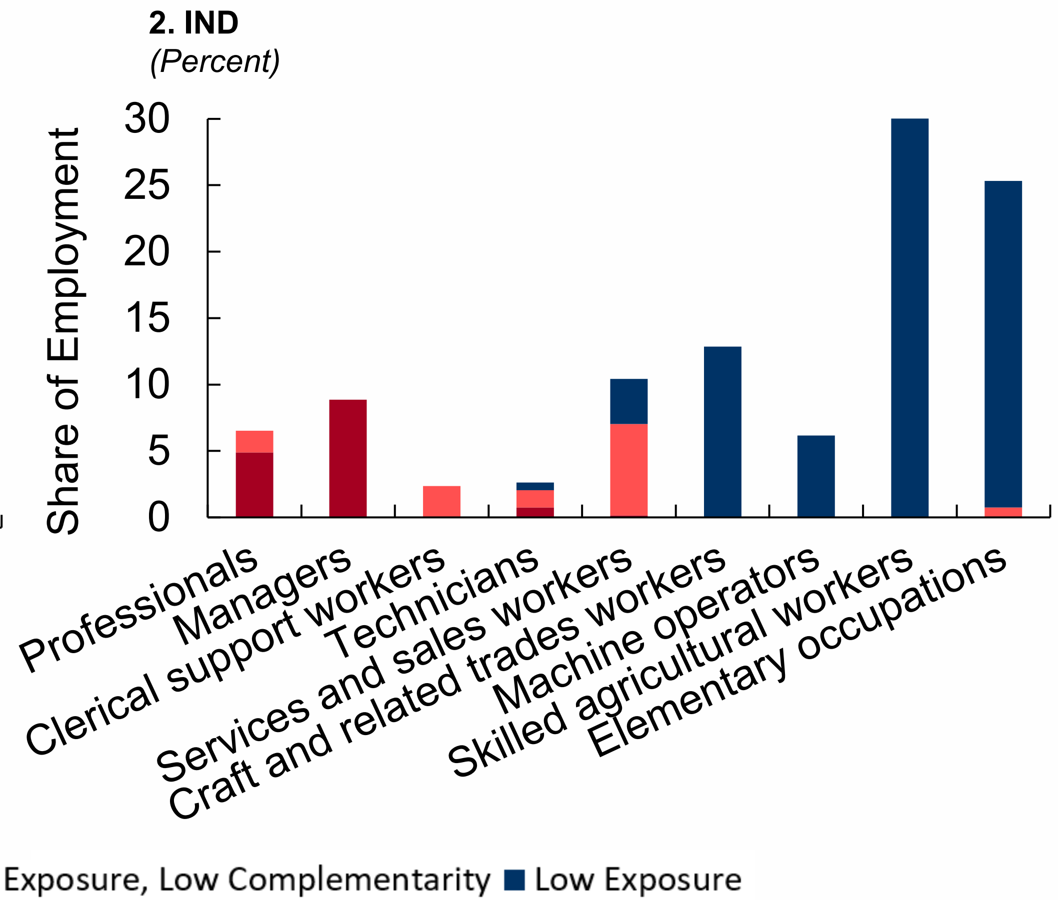
Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); International Labour Organization (ILO); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey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

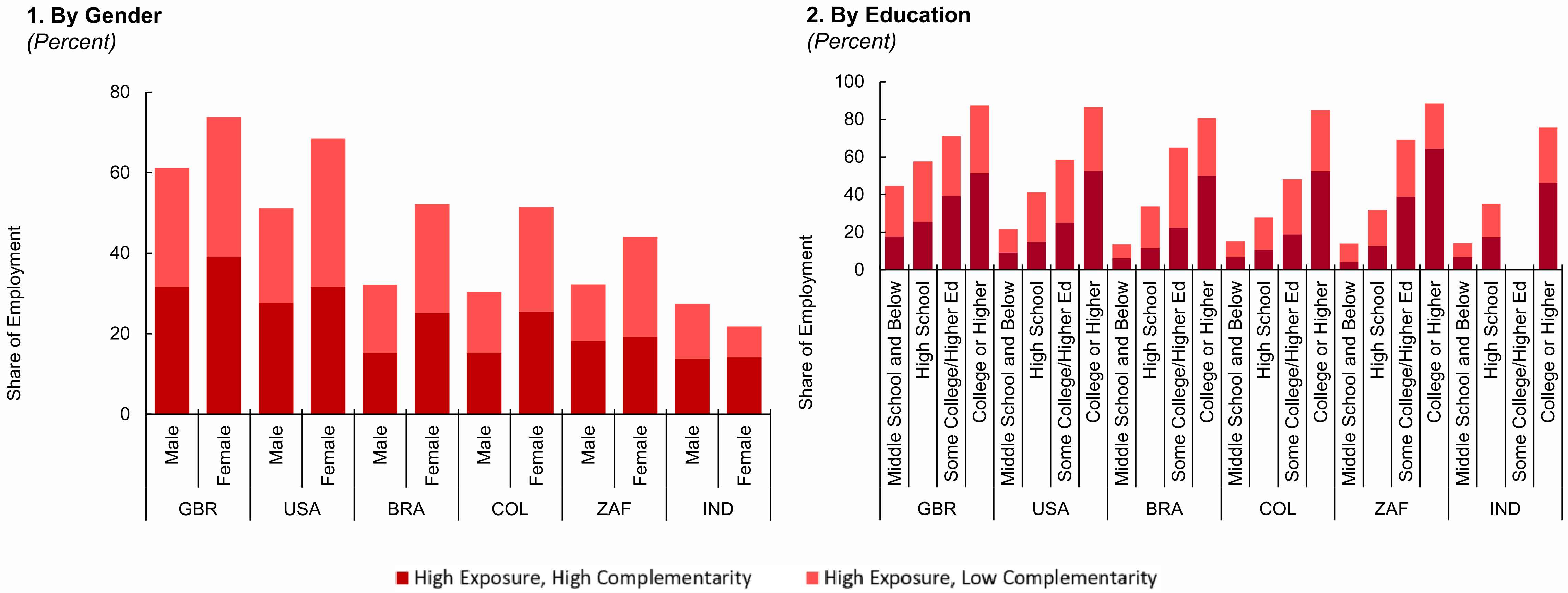




Sources: India Periodic Labour Force Survey (PLFS); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The charts plot the total employment share by each of the nine 1-digit ISCO-08 occupation codes. Country names use International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

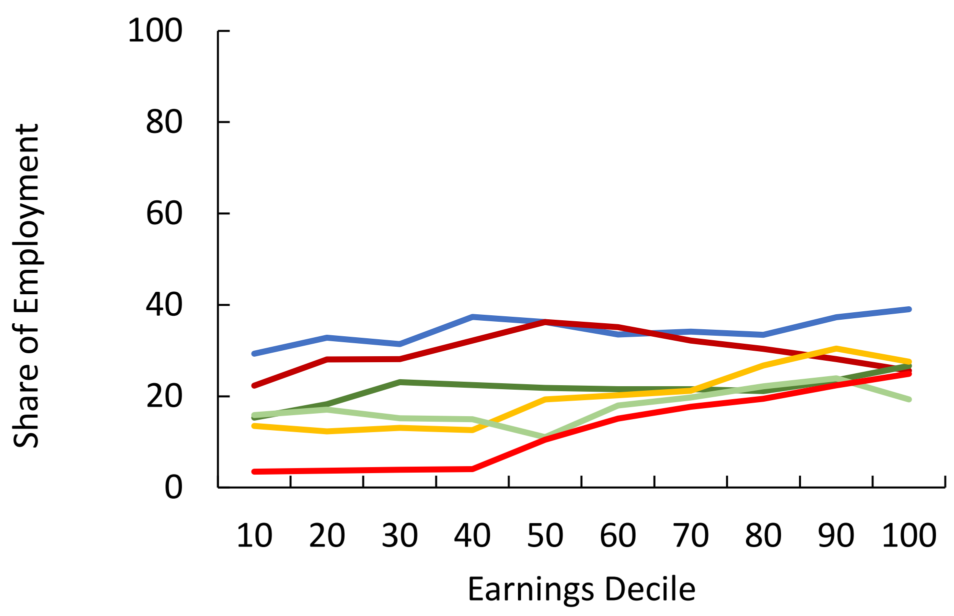


Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: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

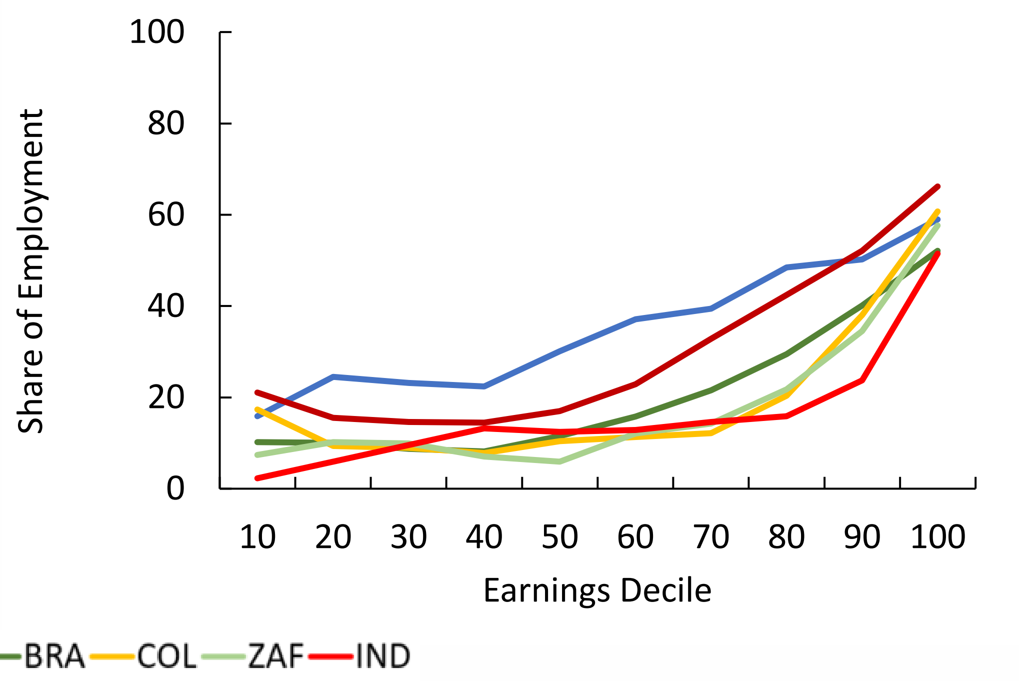
Exposure is spread along the labor income distribution but potential gains from AI are positively correlated with income

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

1. High-Exposure, Low-Complementarity
(Percent)



2. High-Exposure, High-Complementarity
(Percent)

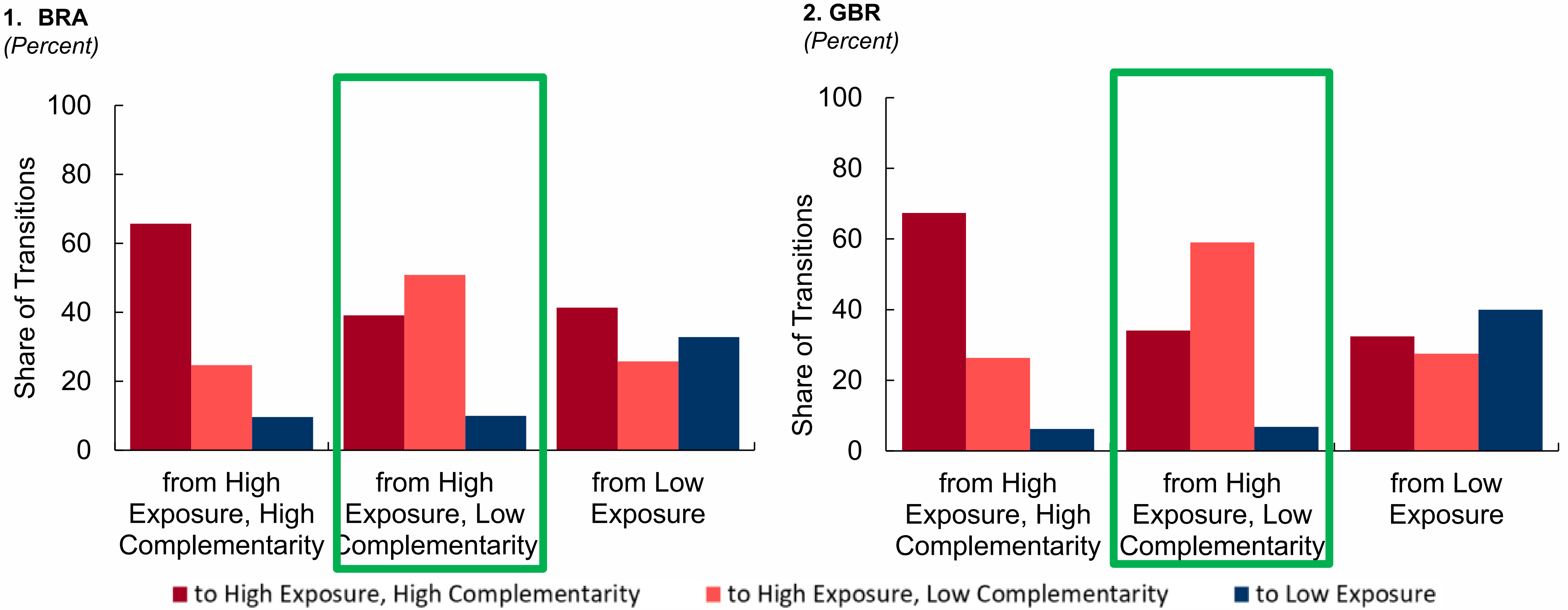


Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); Pizzinelli and others (2023); UK Labour Force Survey (LFS); and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

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

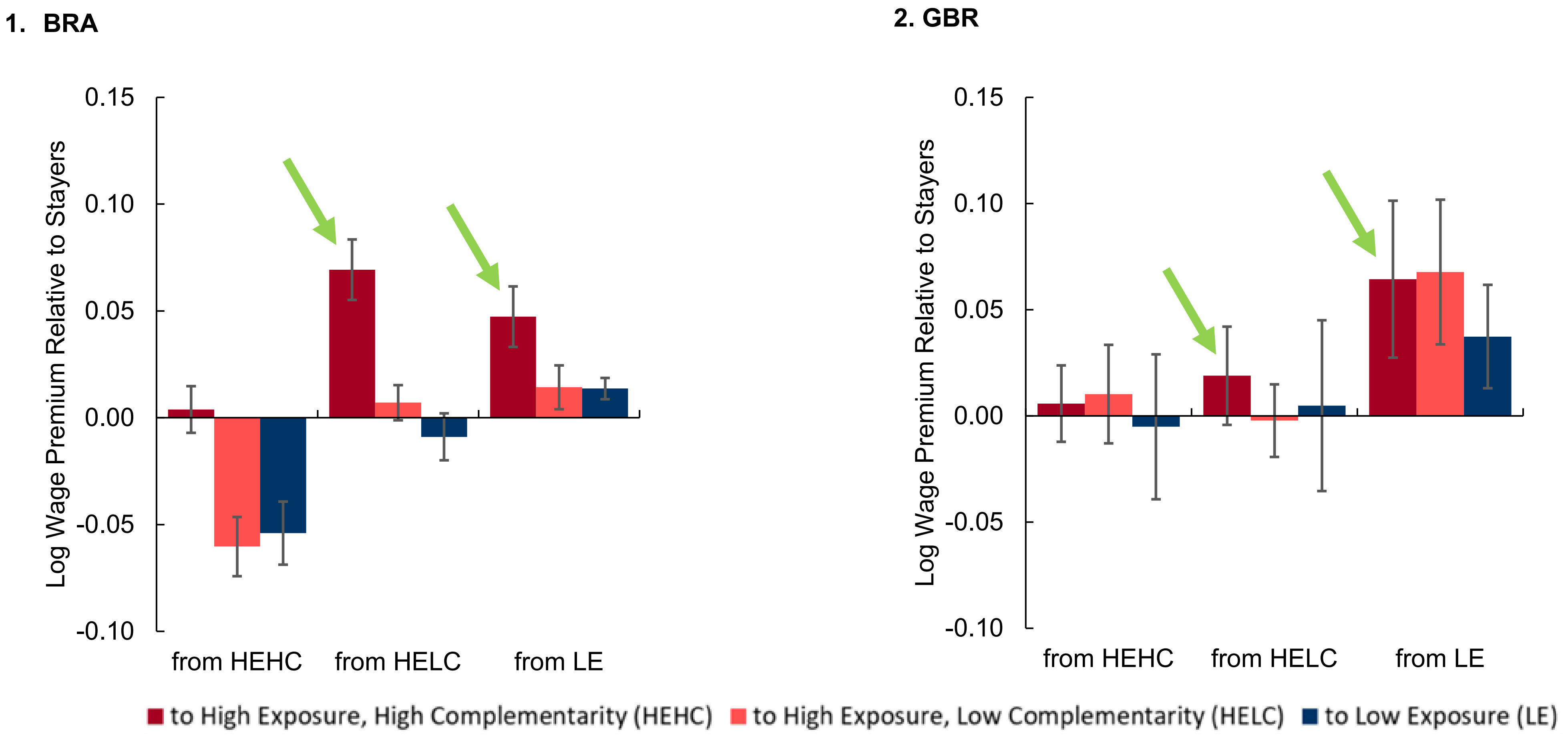
Occupational Transitions for College-Educated Workers



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.

Occupation switches also affect workers' incomes

Estimated Wage Premia from Occupation Changes



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 year, while "to" indicates the exposure category of the occupation the worker transitioned to. The premia are "relative to stayers", that is, they represent the increase or decrease in wages in relation to workers in the "from" category that did not switch occupations over a year. Wage premia are calculated according to the regression specification in Annex 2. 95% confidence intervals for the point estimates are shown in bars. 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

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)

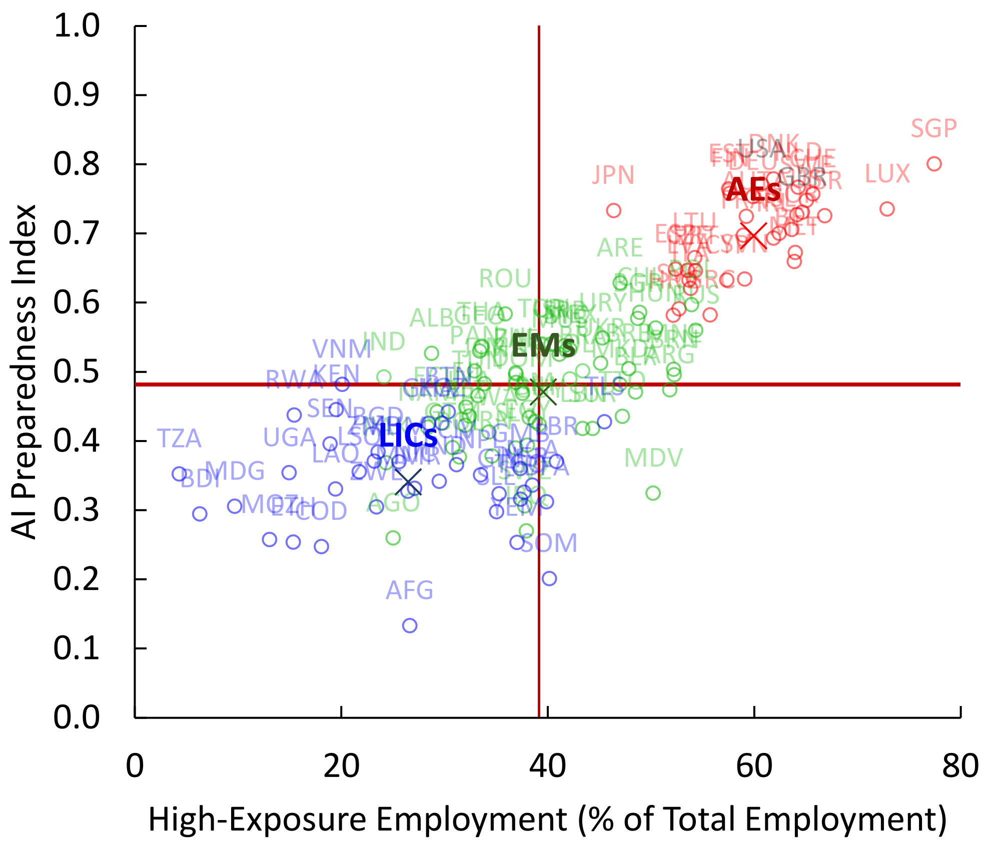
Sources: IMF Staff calculations.
Note: The figure shows the change in the aggregate wage and wealth Gini between the initial and final distribution in each scenario, as well as the change TFP and output. For more details on the model see SDN Annex 4. TFP = total factor productivity.

- **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

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**:

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.

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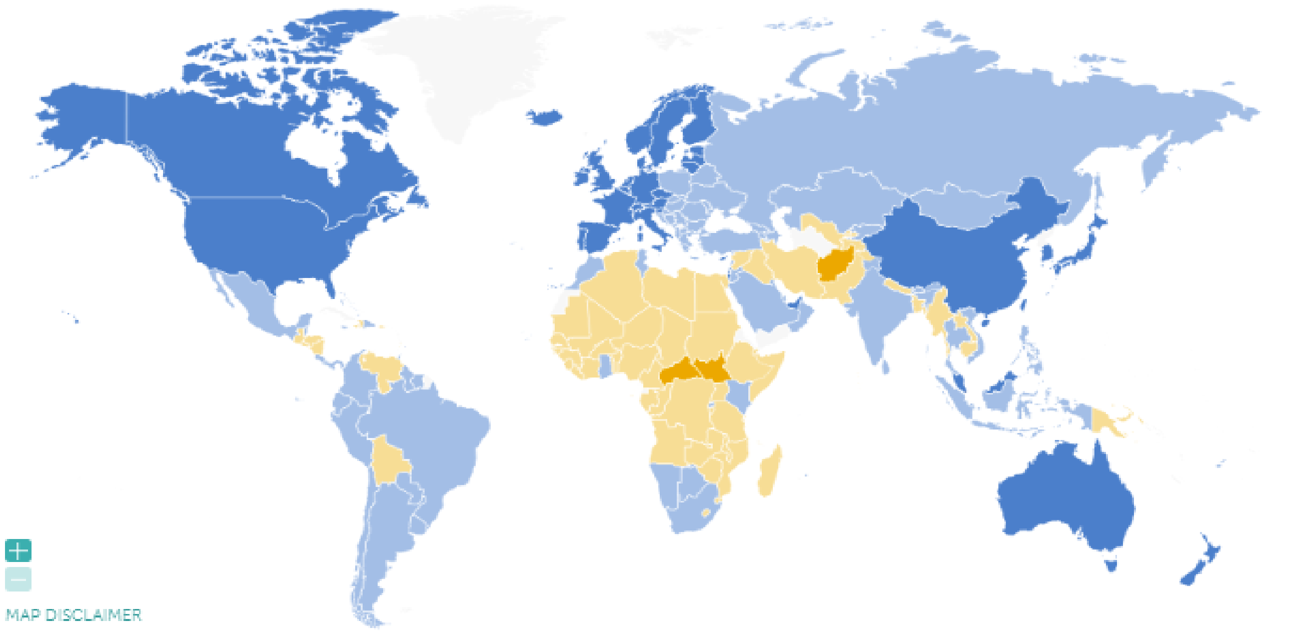
IMF DATAMAPPER | DATASETS | AI PREPAREDNESS INDEX (AIPI) | AI PREPAREDNESS INDEX

AI Preparedness Index

Index

MAP (2023)

● 0.8 and more ● 0.6 - 0.8 ● 0.4 - 0.6 ● 0.2 - 0.4 ● under 0.20 ● no data



MAP DISCLAIMER

LIST (2023)

Country | Region | Analytical group

Country	Value
Afghanistan	0.13
Albania	0.53
Algeria	0.37
Angola	0.26
Argentina	0.47
Armenia	0.49
Australia	0.73
Austria	0.72
Azerbaijan	0.47
Bahamas, The	0.46
Bahrain	0.52
Bangladesh	0.38
Barbados	0.5
Belarus	0.47
Belgium	0.67

Conclusions

AI adoption may generate labor market shifts with significant cross-country differences

- AI offers potential for productivity gains but also poses risks of job displacements.
- AI may lead to a large increase in inequality within and across countries.

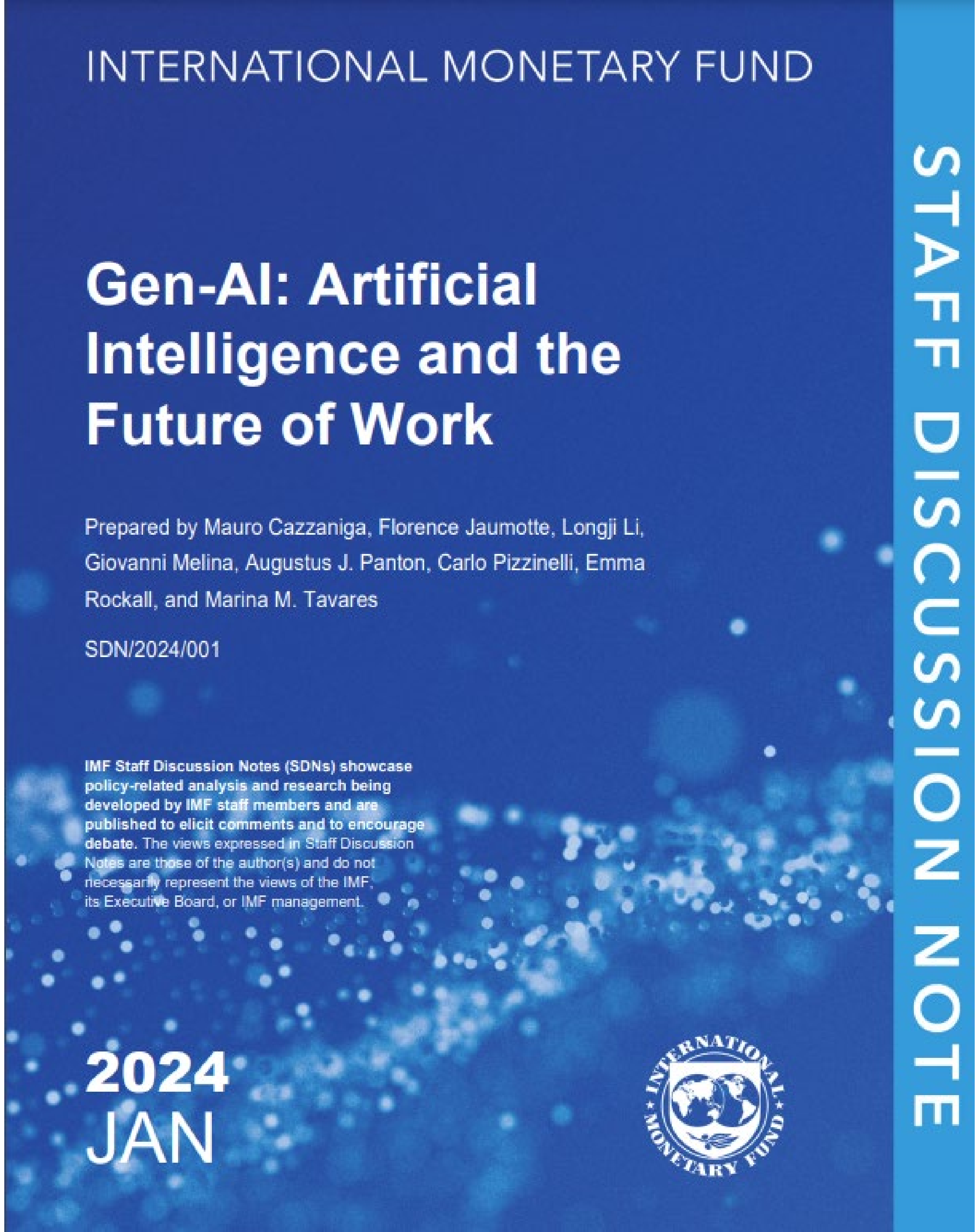
Harnessing the advantages of AI will depend on countries' preparedness

- AEs and some EMs are better prepared (than LICs) to harness AI's benefits while mitigating risks.
- LICs and some EMs should prioritize digital infrastructure and human capital investments.
- AEs and some EMs should invest in AI innovation while advancing regulatory frameworks.

The potential implications of AI demand a proactive approach from policymakers.

- AI-induced labor market disruptions have the potential to create social unrest.
- Policies should promote:
  - equitable and ethical integration of AI
  - train the next generation of workers
  - protect and help retrain workers currently at risk from disruptions.
- AI's cross-border nature creates ethical and data security challenges and calls for international cooperation.

Thank you!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