International Labour Organization

AI, productivity and jobs
What can the Global South expect?

Ekkehard Ernst,
ILO Research Department
ernste@ilo.org

Nigerian Economic Association – 8 Sept 2026

Overview

AI narratives

AI Narratives about jobs:

OpenAI CEO tells Federal Reserve confab that entire job categories will disappear due to AI

Sam Altman also said AI could already diagnose better than doctors, as his company expands into Washington

2025

AUTOMATION

Oxford Study: 47% of U.S. Jobs Could Be Done by Machines

Brian Buntz
September 27, 2013

2013

The Economist

Special report | The impact on jobs

Automation and anxiety

Will smarter machines cause mass unemployment?

2018

AI

Anthropic CEO says AI could wipe out half of all entry-level white-collar jobs

By Ana Altchek and Sarah Perkel

2025

AI narratives | Macroeconomic theory | The task framework | AI exposure measures | Ex-post evidence on AI & jobs | AI policies & governance

Oops: The Predicted 47 Percent of Job Loss From AI Didn't Happen

By Robert D. Atkinson | September 30, 2022

2022

CNN Business Markets Tech Media Calculators Videos

Markets → | | | Fear & Greed Index → | Latest Market News →
DOW 46,381.54 0.14% ▲ | Greed is driving the US market | MacKenzie Scott gives
S&P 500 6,693.75 0.44% ▲ | 63 | Timeline: Jimmy Kimme
NASDAQ 22,788.98 0.70% ▲ | | Jimmy Kimmel's cousin

Business / Tech

Will AI really wipe out white collar jobs? Tech insiders are split

2025

A business journal from the Wharton School of the University of Pennsylvania

KNOWLEDGE AT WHARTON

TOPICS SERIES ARTICLES PODCASTS VIDEOS

AI Can't Replace You at Work. Here's Why.

July 2, 2024 • 4 min read
Updated: July 3, 2024

Valery Yakubovich, executive director of Wharton's Mack Institute for Innovation Management, says that generative AI has a long way to go before it won't require intensive human oversight.

2024

BBC

Home News Sport Business Innovation Culture Arts Travel Earth Audio Video Live

AI will create as many jobs as it displaces - report

17 July 2018

Share Save

2018

The New York Times

Artificial Intelligence › | Chatbots for Financial Advice | A.I. Influencers | 'Open-Source' OpenAI | The 'Hard Tech' Era | '90s Nostalgia

The A.I. Revolution Will Change Work. Nobody Agrees How.

The tally of how many jobs will be "affected by" world-changing technology is different depending on who you ask.

Share full article

AI Narratives about artificial general intelligence (AGI):

EDITORS' PICK | INNOVATION > CONSUMER TECH

OpenAI CEO Sam Altman: 'We Know How To Build AGI'

By John Koetsier, Senior Contributor. © Journalist, analyst, author, podcaster.

Published Jan 06, 2025 at 01:15pm EST, Updated Jan 06, 2025 at 02:28pm EST

Share Save Comment

…by 2030..

Demis Hassabis

Google DeepMind CEO Demis Hassabis. Google

AGI will arrive "in the next five to ten years," Demis Hassabis — the CEO of Google DeepMind and a recently minted Nobel laureate — said on the April 20 episode of 60 Minutes. By 2030, "we'll have a system that really

… in our lifetime…perhaps

Andrew Ng

AI researcher Andrew Ng. Steve Jennings / Stringer/Getty Images

Leading AI researcher Andrew Ng is a little more conservative in his estimates about AGI. He's described it as a form of intelligence that can do "any intellectual tasks that a human can," whether that's driving a car, flying a plane, or writing a Ph.D. thesis.

And he's not convinced we'll get there soon. "I hope we get there in our lifetime, but I'm not sure," he said, adding that people should be skeptical of companies that claim AGI is imminent.

International Labour Organization

TechCrunch

Rodney Brooks pours cold water on AGI predictions ...

"Einstein predicted gravitational waves in 1916. It took ninety nine years of people looking before we first saw them in 2015 (...) Some things just take a long time, and require lots of new technology, lots of time for ideas to ferment, and lots of Einstein and Weiss level contributors along the way. I suspect that human level AI falls into this class. But that it is much more complex than detecting gravity waves, controlled fusion, or even chemistry, and that it will take hundreds of years.

Rodney Brooks, Professor of Robotics (emeritus) at MIT

What do we know about AI exposure and jobs?

How to measure the impact of AI on jobs and productivity?

Previous waves of automation

Ex-ante AI exposure measures

Ex-post job measures

Company surveys

Previous waves of automation suggest strong impact on jobs in emerging economies: Job losses from robotization

Dependent variable: Employment (in logs)	World		Developed countries		Developing countries	
robot stock	−0.055**	−0.044**	**−0.029*****	−0.034***	**−0.343*****	-0.329
	(0.028)	(0.018)	(0.009)	(0.009)	(0.112)	(0.480)
robot stock × labour intensity		-0.023		0.012		-0.011
		(0.044)		(0.019)		(0.411)
labour intensity	0.007	0.015	0.002	0.001	-0.016	-0.010
	(0.008)	(0.015)	(0.005)	(0.005)	(0.021)	(0.217)
N	477	477	360	360	117	117
R^2	0.84	0.85	0.80	0.80	0.35	0.38

Note: Regressions include country and industry fixed effects. Trends are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: $*$, $**$, $***$ indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage. Estimates are weighted by sectoral employment in 2005.

Estimated equation:

$$N_{ij} = \beta_0 + \beta_1 robots_{ij} + \beta_2 robots_{ij} \times li_{2005} + \beta_3 li_{2005} + \beta_4 VA_{ij} + \beta_5 W_{ij} + u_{ij}.$$

What are AI exposure measures?

Task-based exposure measures ("cookbook"):

1. Identify task-level information from databases about occupations (e.g., O*NET, ISCO, STEP, PIAAC).

2. **Assess whether specific tasks (e.g., writing reports, data analysis) could potentially be automated by AI/GenAI/computers now or in the future.**

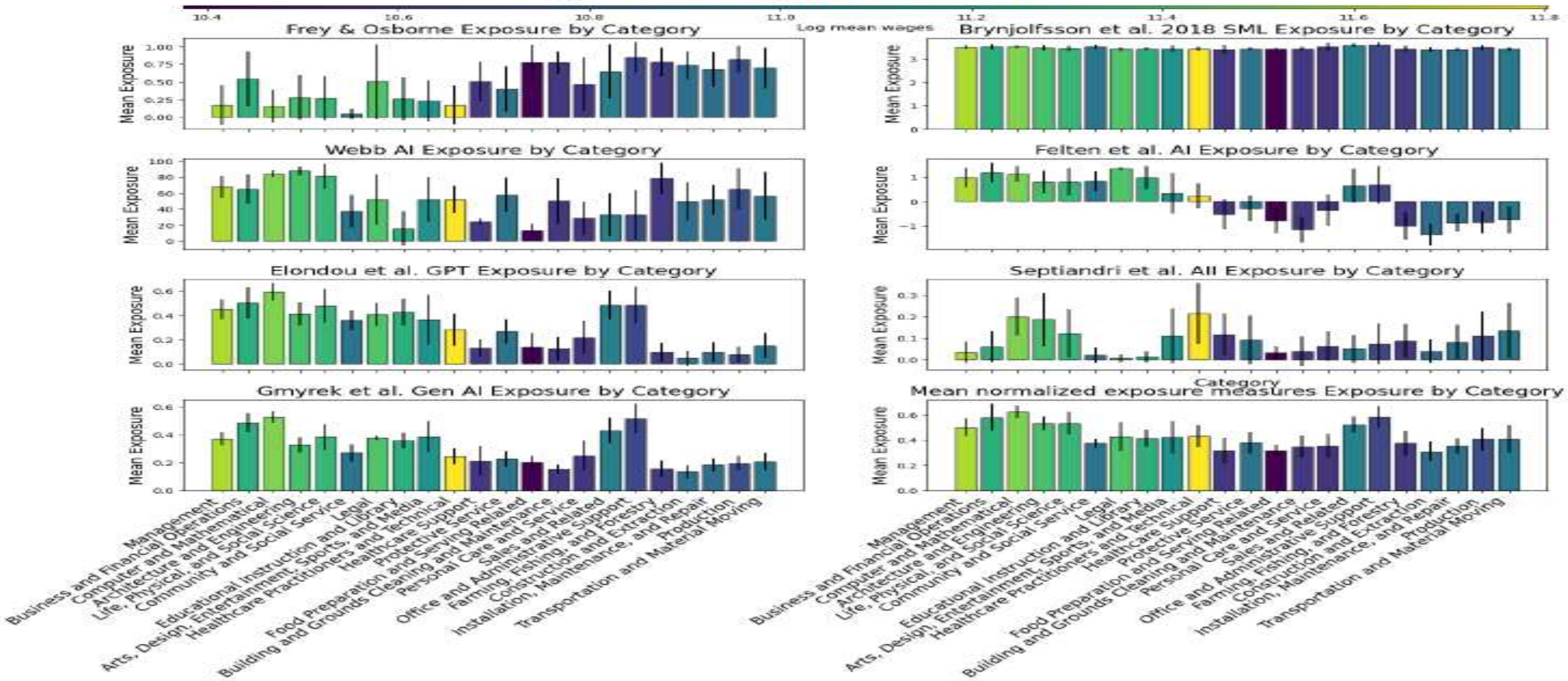
3. Aggregate task-level exposure to the occupation level, providing insights into how AI might impact jobs or occupational clusters

4. Link the exposure measures to current employment estimates

e.g. Autor, Levy & Murname (2003) on computerization, Autor (2013), Frey and Osborne (2013), Brynjolfsson et al. (2018), Felten et al. (2021)

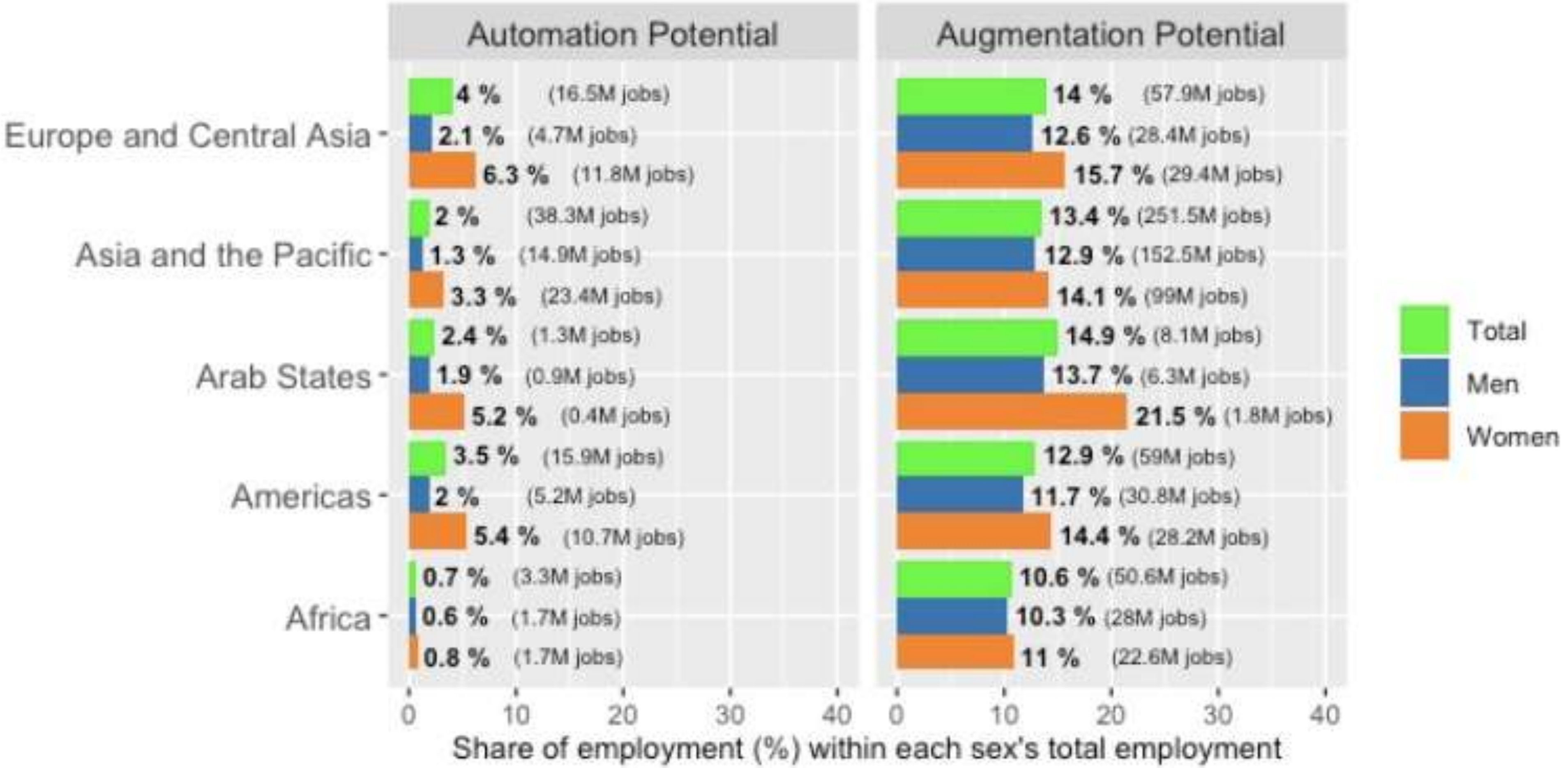
Overview of (ex-ante) AI exposure measures: Shifting consensus among experts

Figure 1: AI-exposure measures



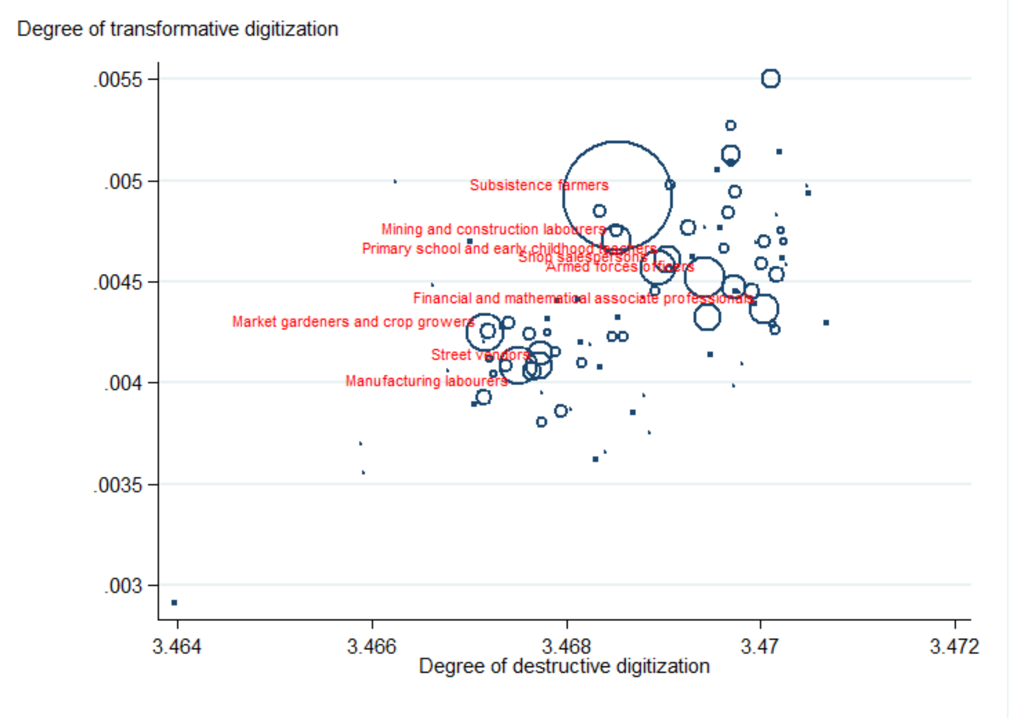
Share of earnings associated with entry-level skills

GenAI transforming jobs more than destroying them, especially in the Global South

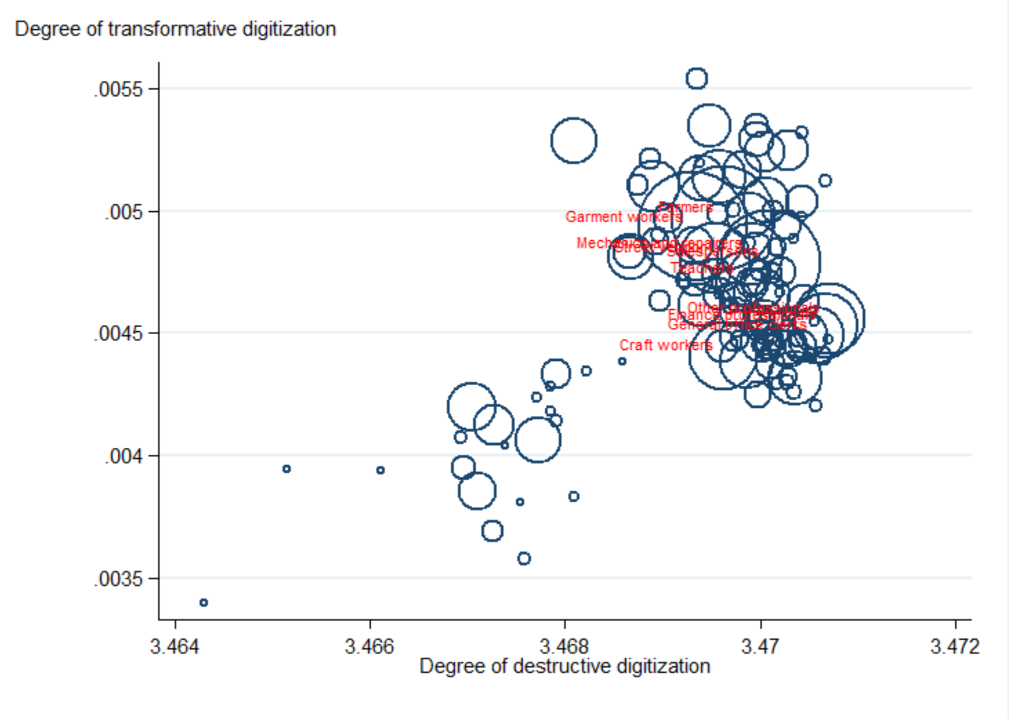


Speed of transformation will determine polarisation

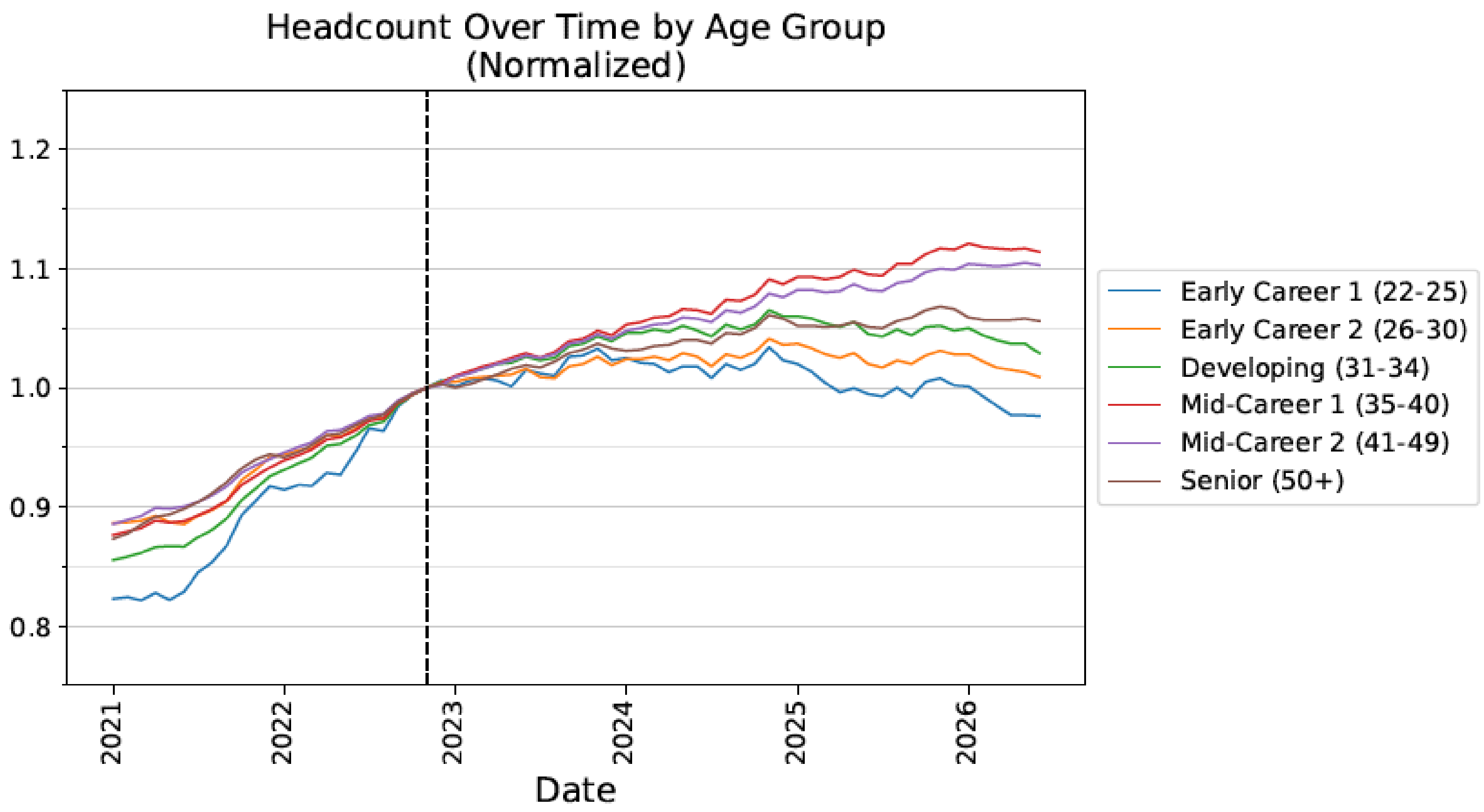
Laos



Vietnam



Are young people particularly affected? Evidence from the US



International Labour Organization

Which workers are most exposed?*

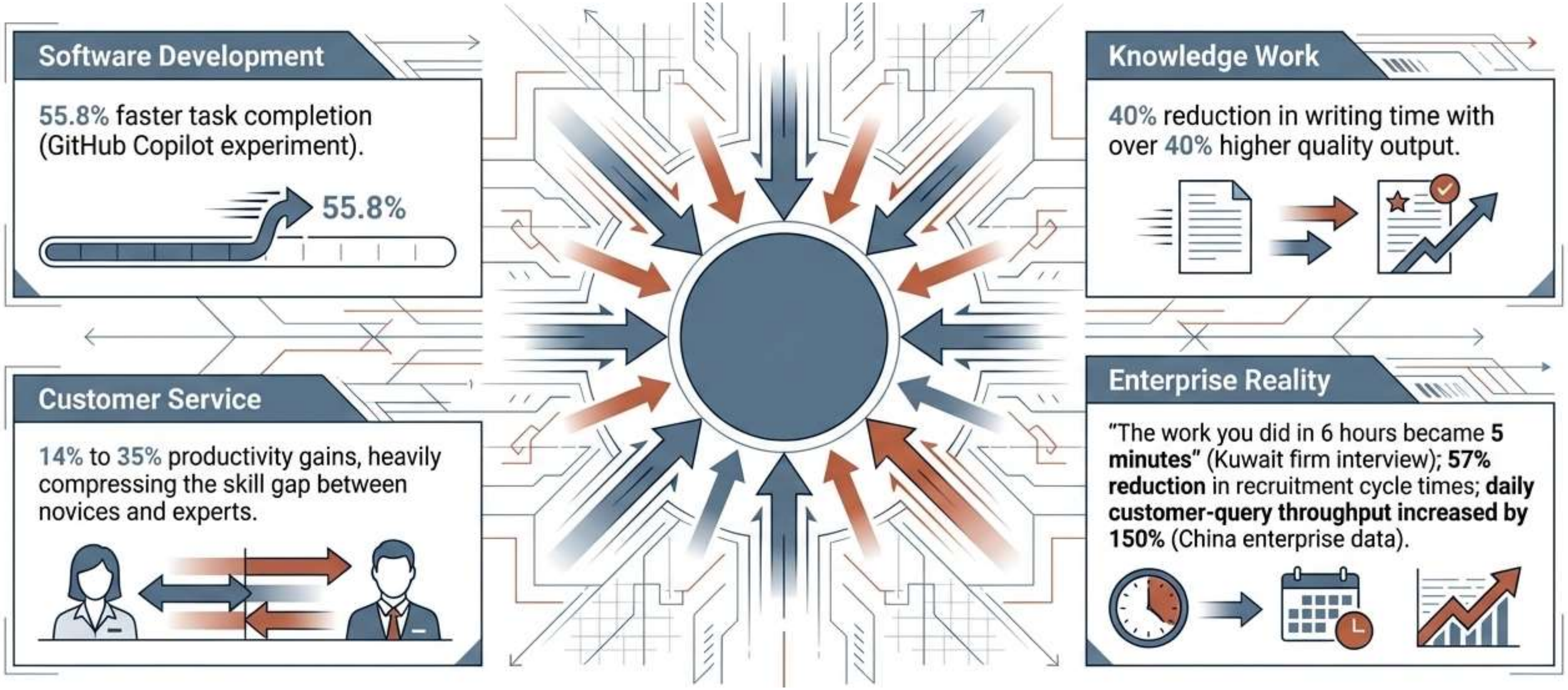
- Workers in non-routine occupations <u>are</u> exposed!
- Advanced economies more than developing economies
- Urban areas more than rural areas
- Younger workers more than older workers
- Women more than men
- Higher-educated more than lower-educated workers
- High-skilled more than low-skilled workers
- Certain professions — e.g. administrative roles, paralegals, customer service representatives, translators — are especially exposed

***based on convergence of the most prominent AI measures**

The AI aggregation paradox

Evidence from company surveys

Individual task execution is experiencing unprecedented acceleration



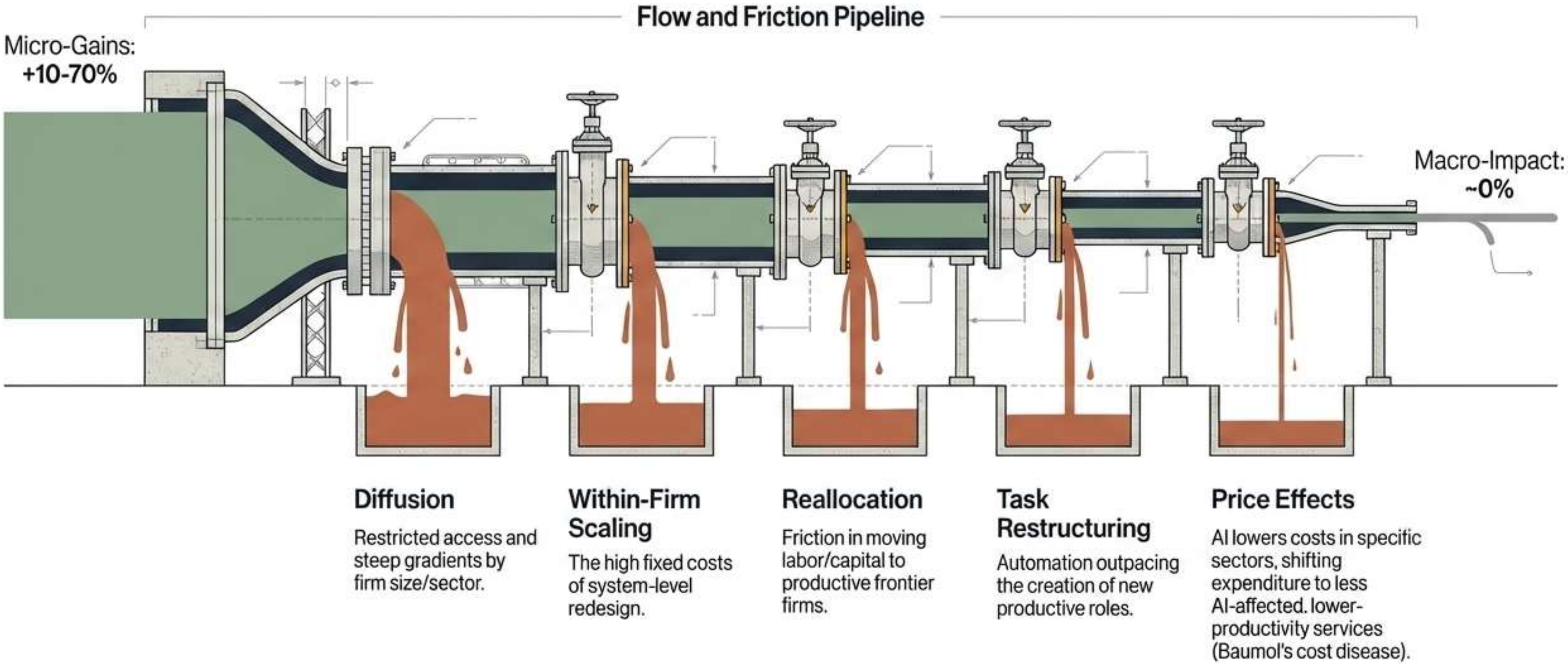
Clear micro-evidence: Task execution can be improved by 10-70% for well-defined and text-intensive tasks

Substantial productivity gains, were measured in Chinese companies

Firm / sector	Metric	Reported impact
Digital manufacturer	Lighthouse factory production efficiency; parameter changeover time	+30% (client factories ~20%); 120 → 60 minutes
Insurance company	Daily customer queries handled by 300 staff	6,000 → 15,000 (+150%)
Giant insurance group	Recruitment cycle time	30 → 13 days (−57%)
Talent management firm	Projects per manager; core efficiency metrics	2–3 → 5–6 projects; +30–100%
HR services firm	R&D man-hours; per-capita customer-service output	−30% (Q1); +28% (Q3)
Ed-tech company	Service pricing; AI study-room operating costs	Halved; 80% below traditional tutoring

All figures self-reported by firm representatives; a travel firm also estimates AI data-handling equivalent to 5–6 full-time employees

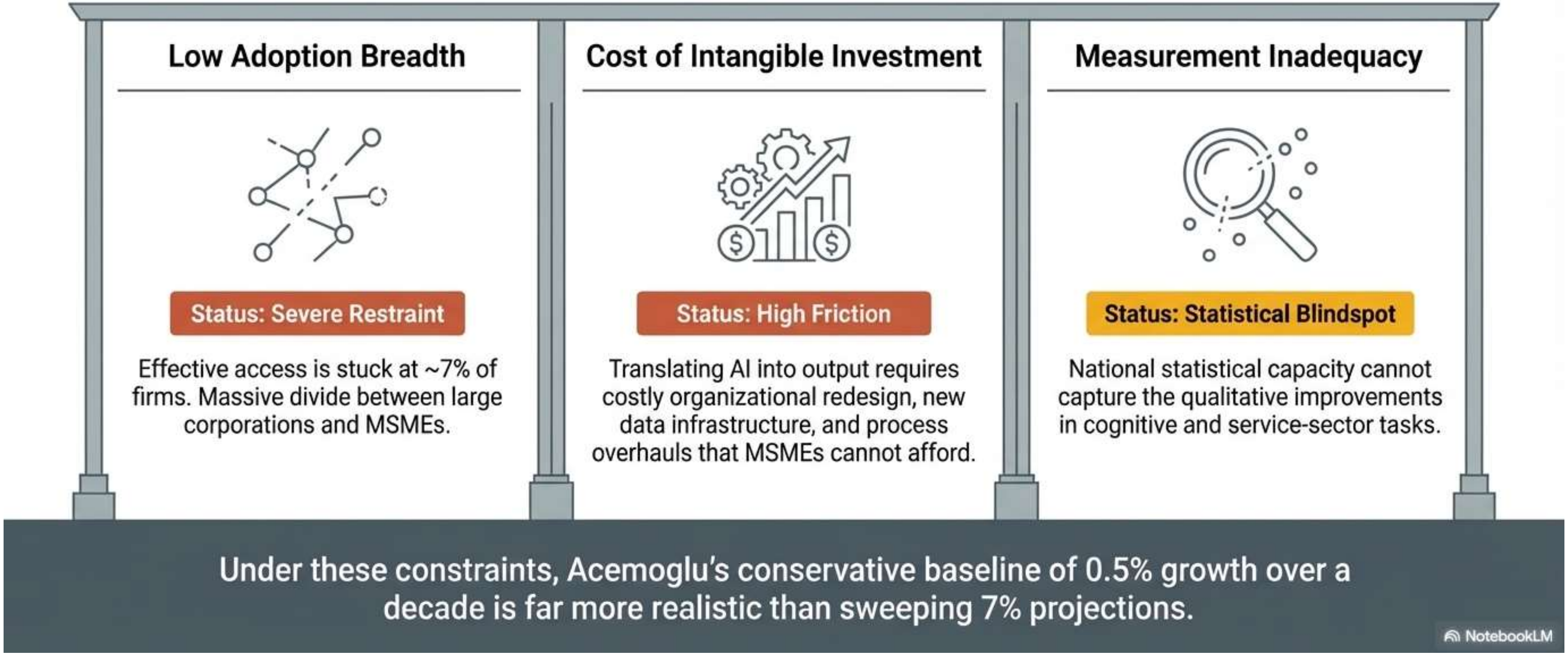
Productivity leaks through critical channels when aggregating



General purpose technologies follow a predictable path

	First deployment	Time to macro impact	Key bottleneck
Electrification	1882	~ 40 years (1920s)	Physical redesign of factor floors and grid buildout
ICT/Internet	1970s	~ 15-25 years (1990s)	Hardware costs, digital literacy, and business process re-organisation
Artificial Intelligence	(first wave) 2012 (GenAI) 2022	Not yet observed	Complementary skills, organisational redesign, and compute/data costs

Three bottlenecks prevent macroeconomic realization today



Tool-led gains cannot move the company P&L: The arithmetic caps them long before execution quality becomes the binding constraint

30%
Measured gain on the task
Mid-range of the experimental evidence

›

× 20%
Share of tasks actually amenable
The rest of the job is unaffected by the tool

›

– 10%
Verification and rework tax
Checking and integrating AI output is not free

›

× 30%
Share of the workforce actively using it
Generous vs. observed enterprise adoption

=
1.0%
one-time level effect on company throughput

At today's typical enterprise adoption of ~6%, the same arithmetic yields 0.2%

A rounding error against a 12% EBIT margin — and it does not compound. Doubling the licence budget doubles a number that is already immaterial. This is why four out of five adopters truthfully report "no measurable effect" while their own pilots truthfully report 30% gains.

Implication for companies

Any AI business case built on multiplying a task-level percentage by headcount is arithmetically unsound. The company-wide, durable gain has to come from somewhere else: from redesigning how the work itself is organised, and from that redesign travelling across the organisation. That is a different channel with different economics — and different failure modes.

The measurement gap creates an illusion of impact

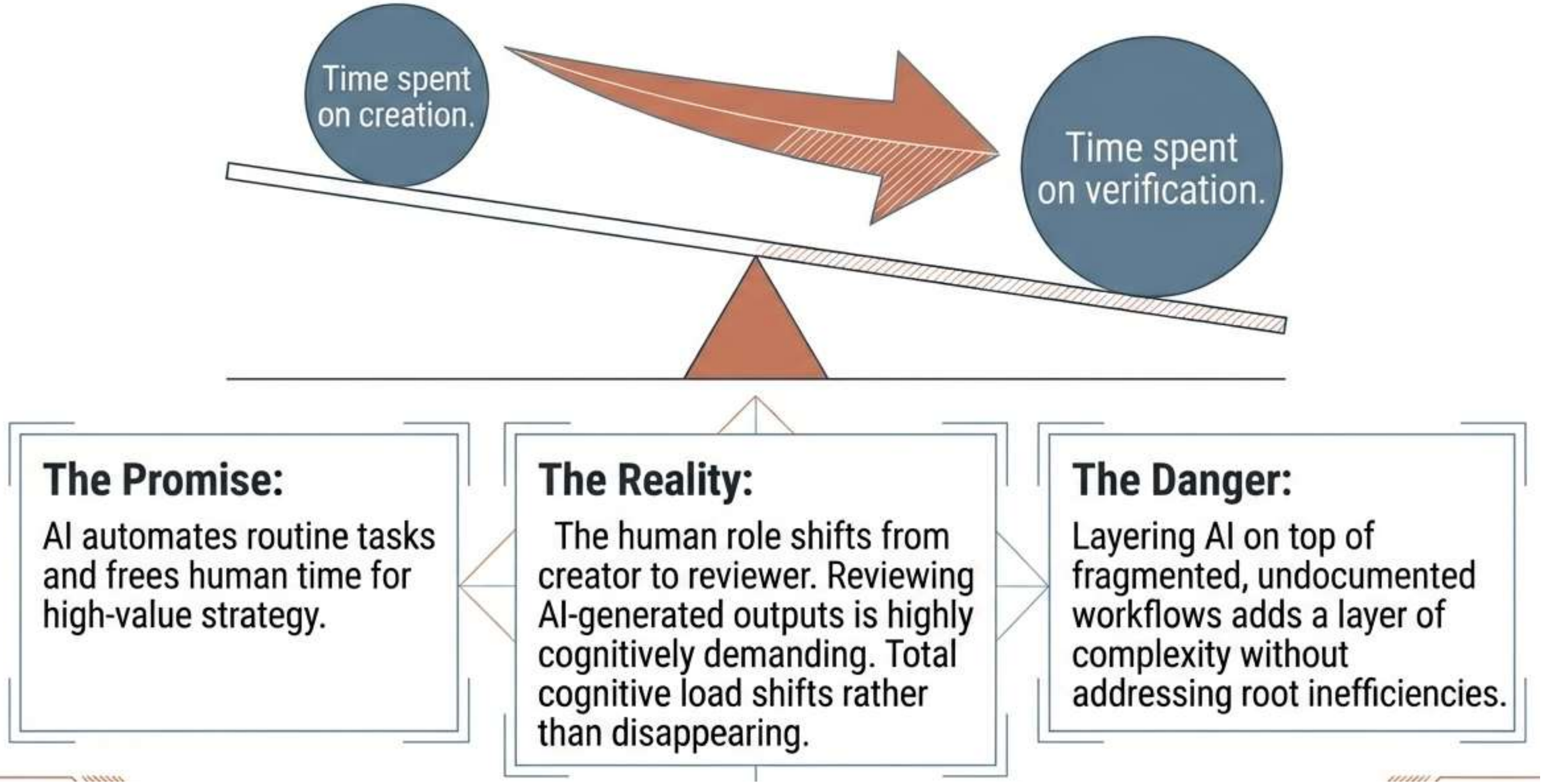
74% of reported enterprise productivity impacts remain entirely unverified (Kuwait data).

Unverified claims occur because workflows are not instrumented, baselines are missing, and data remains siloed.

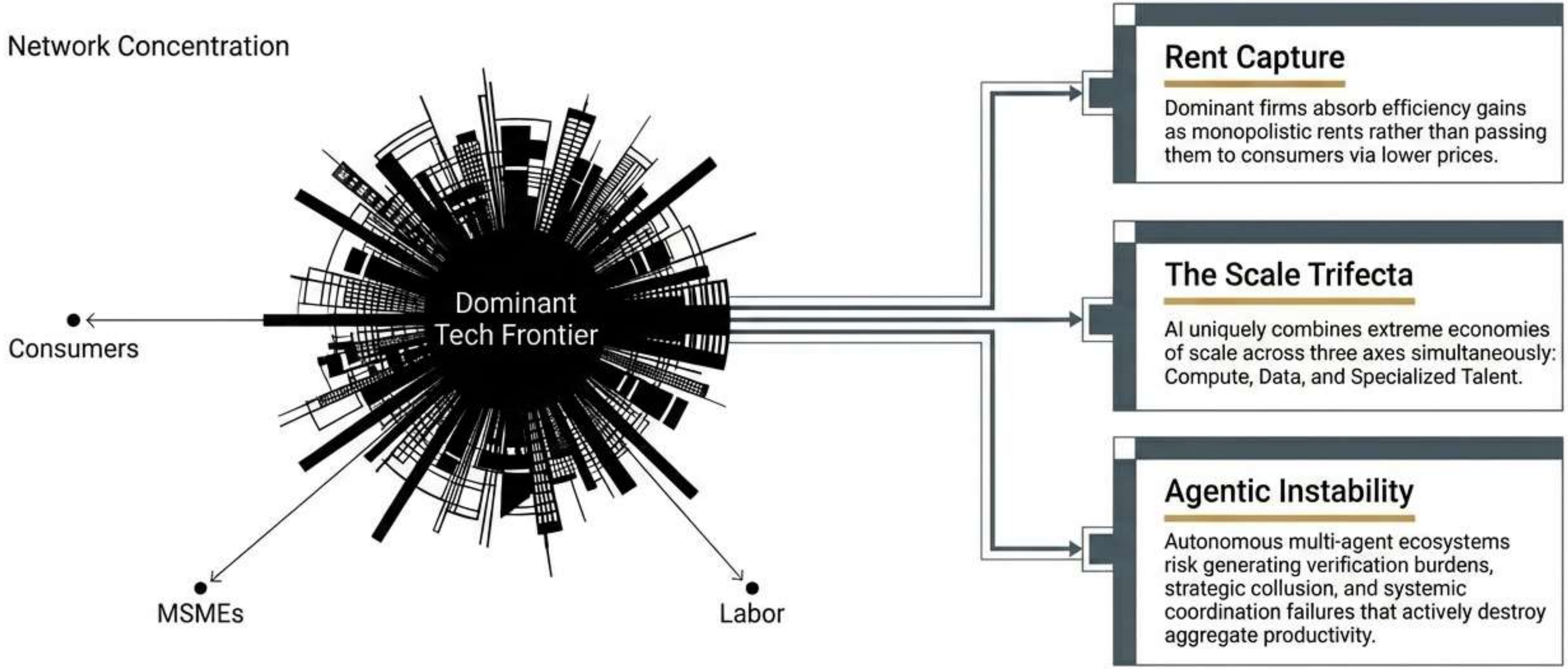
Where verification does exist (the 26%), the gains are monumental: 60-98% reductions in task time for targeted processes.

Takeaway: Firms are committing significant resources to AI without the measurement discipline required to move from pilots to scalable performance.

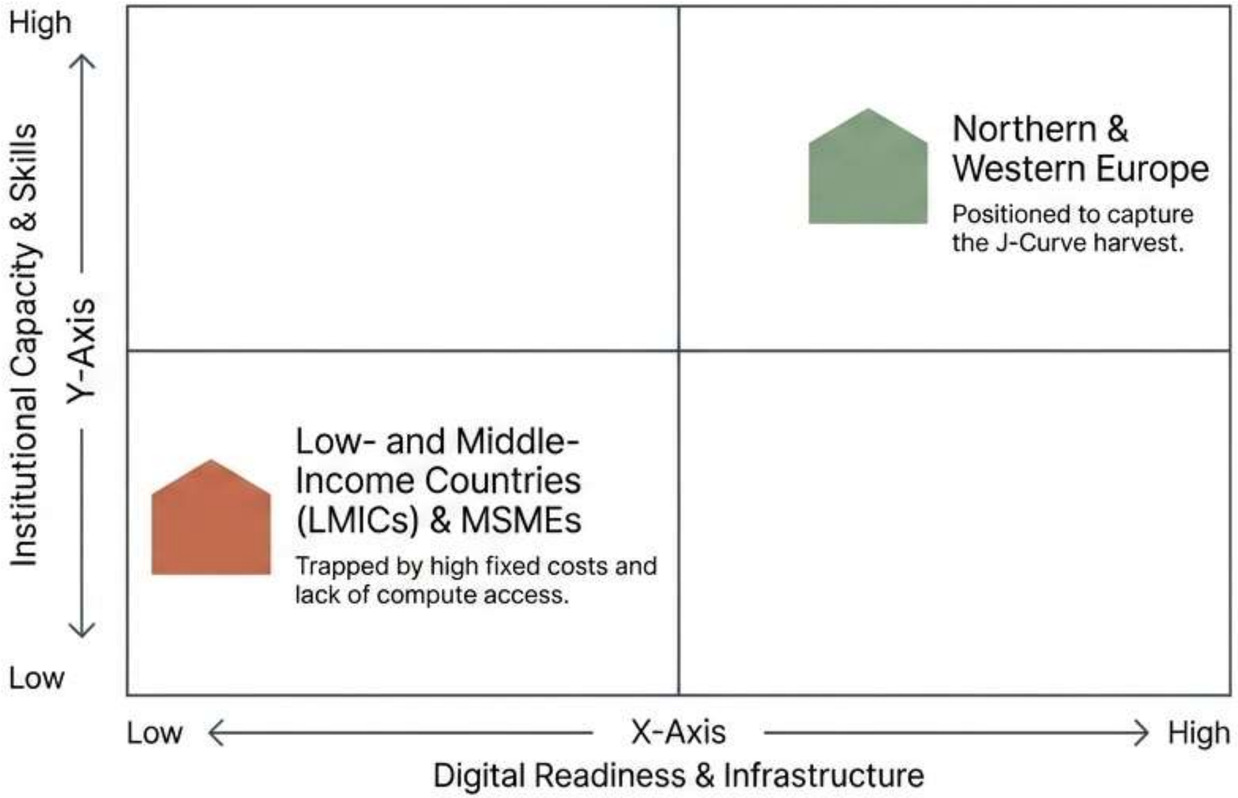
Task automation triggers the efficiency paradox



Entrenching market concentration and agentic eco-systems create risks for SMEs to adopt tools and create value



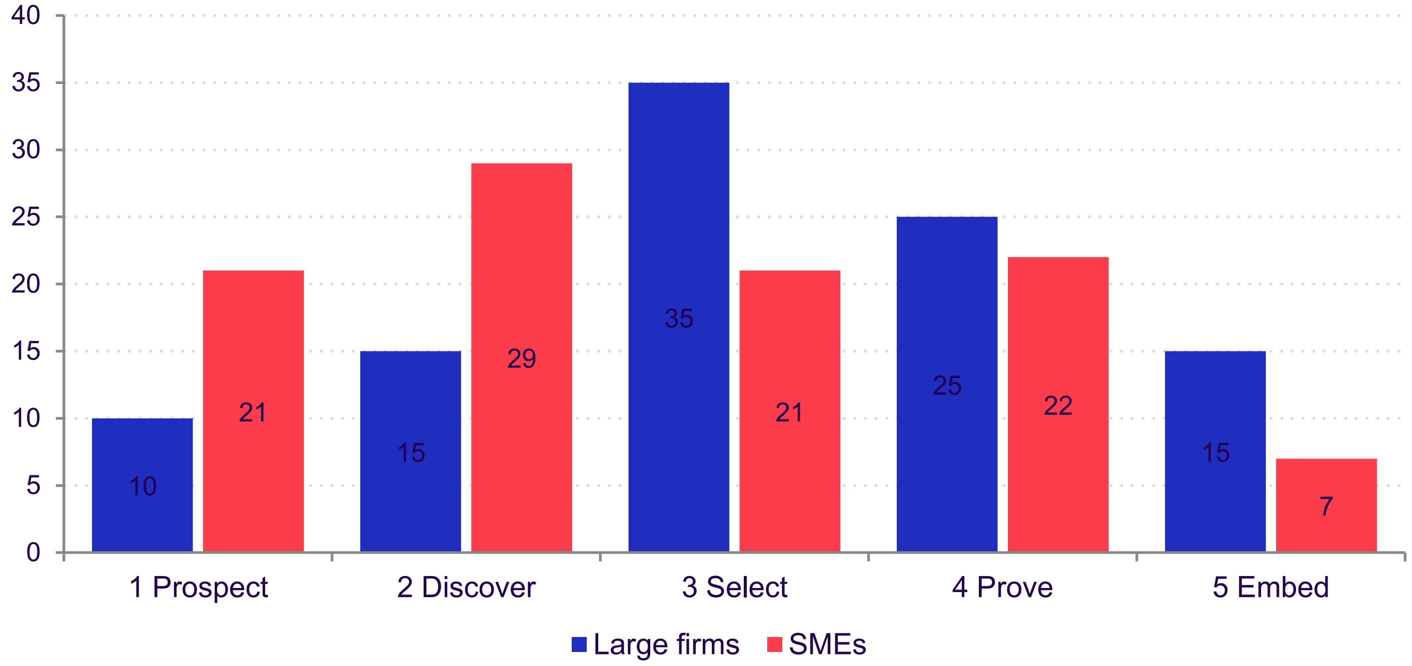
Structural divide threaten to permanently widen cross-country productivity gaps



Key Insight: AI exposure does not automatically yield productivity convergence. Without targeted public investment, economies lacking digital foundations and active labor market policies policies will be structurally excluded from the aggregate gains.

International Labour Organization

A two-speed economy is emerging – K-shaped economy



Share of enterprises in each adoption phase, by size group (per cent). Phases run from no ongoing AI projects (Prospect) to AI integrated into core processes (Embed).

Formal AI usage policy

45% large firms **14%** SMEs

AI training programmes for staff

65% large firms **29%** SMEs

Policy and training shape whether firms can deploy AI responsibly, manage risks and build the internal capability needed to scale.

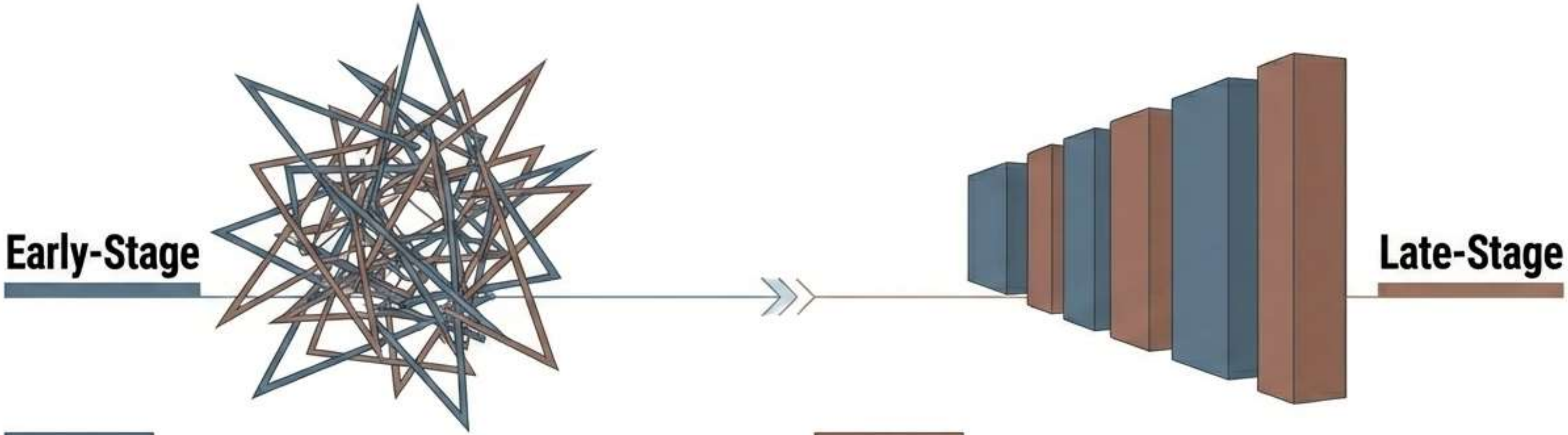
Without massive capital for data infrastructure and governance, SMEs face a structural disadvantage in capturing AI value.

Five recurring implementation challenges among Chinese companies

Challenge	Firms citing	Illustrative examples
Output quality & reliability	8+	Hallucinations; sub-95% customer-service accuracy; prohibitive correction costs
Workforce skills & resistance	6+	Age divide; missing "AI mindset"; explicit and passive resistance
Regulatory & data security	6+	Financial data firewalls; multinational headquarters restrictions; client privacy
System integration & governance	5+	Legacy systems; scattered data; cross-departmental coordination
Cost & ROI concerns	5+	High current investment with low immediate output; costly tool licensing

The regulatory landscape is multi-layered — national rules, sectoral regulation (especially in finance) and multinational corporate policies all shape the boundaries of permissible AI use.

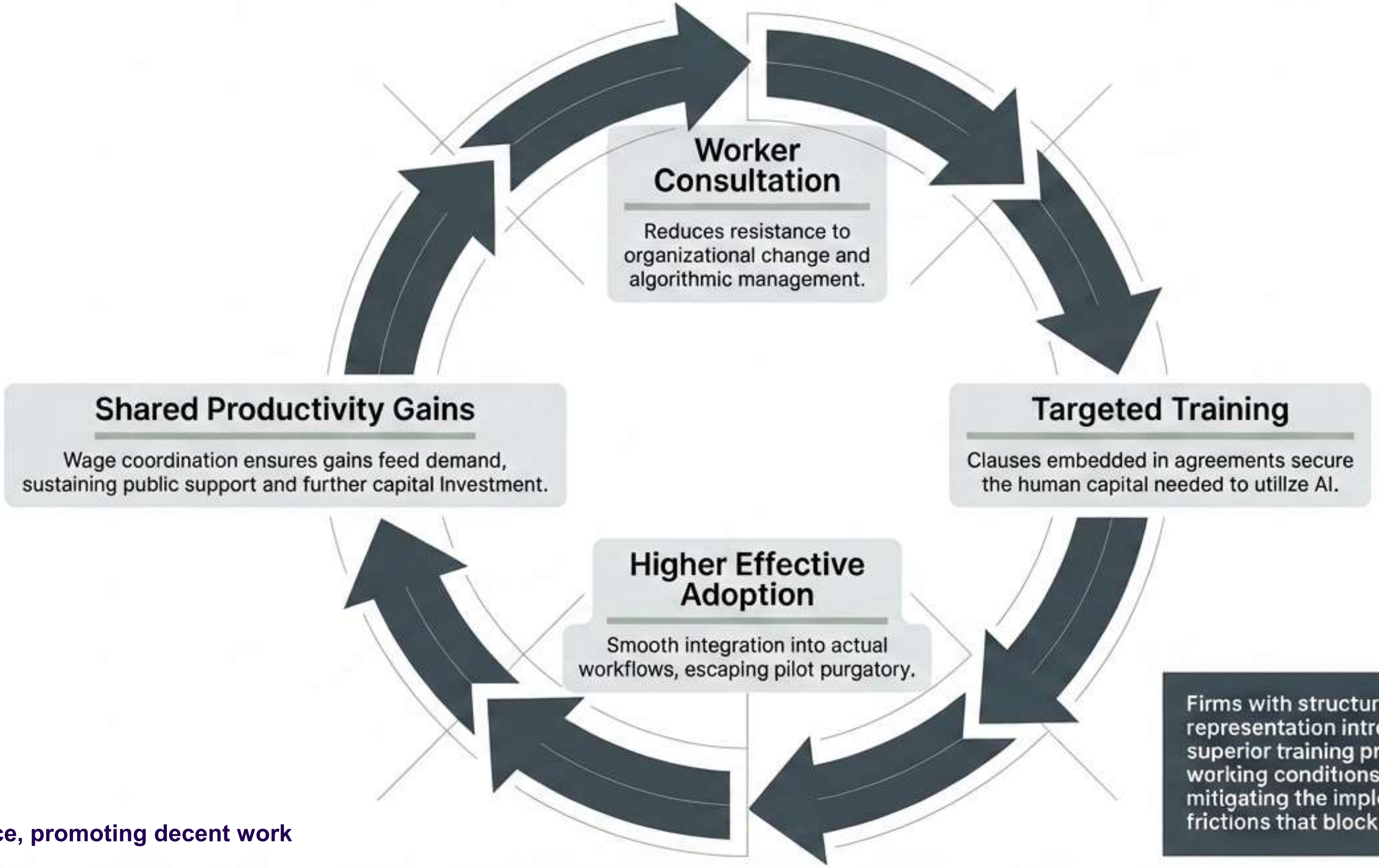
As organisations mature, their binding constraints flip



Early-Stage Constraints (Internal Roadblocks):
- Fragmented data quality and legacy systems.
- Lack of 'AI mindset' and specific prompt/ evaluation skills.
- Employee resistance and displacement anxiety (39% of surveyed professionals anticipate income declines).

Late-Stage Constraints (External Walls):
- Regulatory approval processes and compliance.
- Strict data residency and security requirements.
- Vendor lock-in and limited audit rights for black-box models.

Collective bargaining helps accelerating investment and restructuring



Firms with structured worker representation introduce AI with superior training provisions and working conditions, directly mitigating the implementation frictions that block scaling.

What do we learn about policy priorities from company surveys?

Strengthen enabling conditions, not specific tools

i. Strengthen data foundations

•Support shared or sector-level data infrastructures, particularly for SMEs

•Promote interoperable data standards and practical data-governance guidance

•Reduce the cost and complexity of building foundational data capabilities

ii. Build skills and organizational capability

•Practical, use-case-oriented AI skills rather than abstract certifications

•Capacity to evaluate vendors, design pilots and assess business cases

•Targeted support for SMEs, where limited internal expertise amplifies risk

iii. Improve measurement and accountability

•Simple, standardized measurement templates tied to named workflows

•Guidance on baselines and tracking outcomes over time

•Approaches that distinguish verified results from perceived benefits

iv. Reduce regulatory and ecosystem frictions

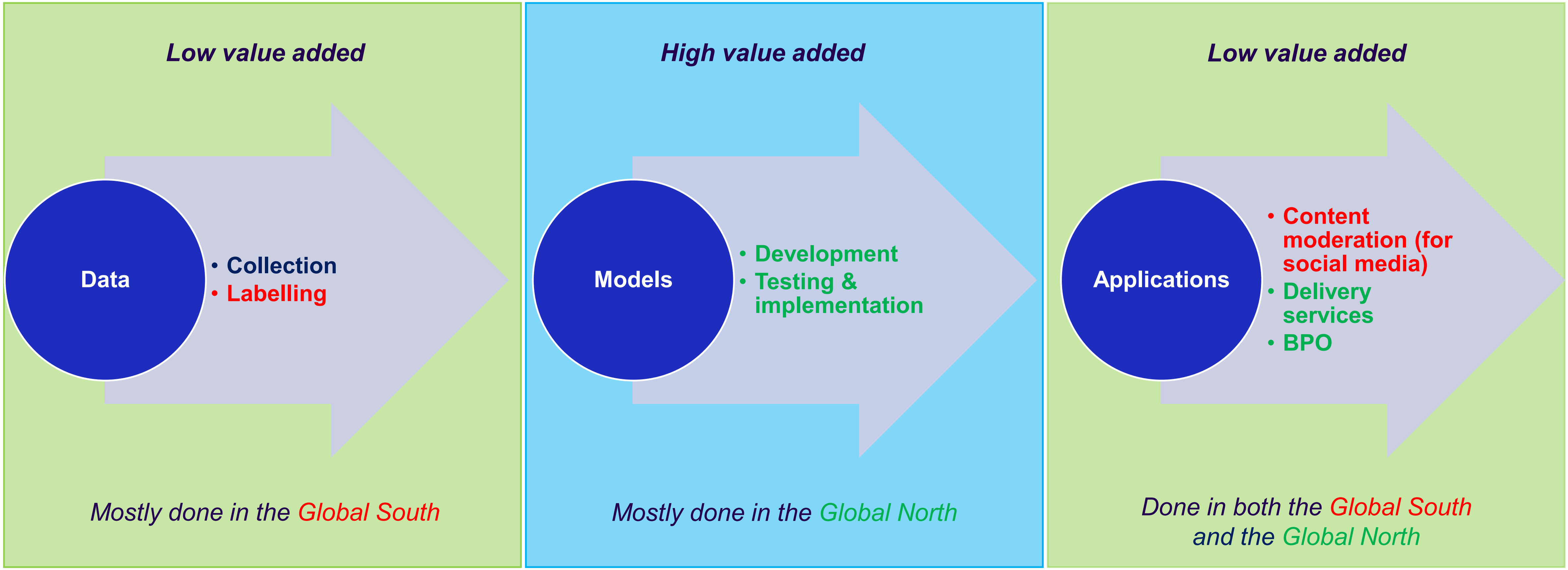
•Clarity on data residency, cloud use and compliance responsibilities

•Time-bound testing environments and trusted mechanisms to assess suppliers

•Lower transaction costs – particularly for smaller firms – without weakening safeguards

The challenge for the Global South

Moving up the AI supply chain: Value added created mostly in the Global North…

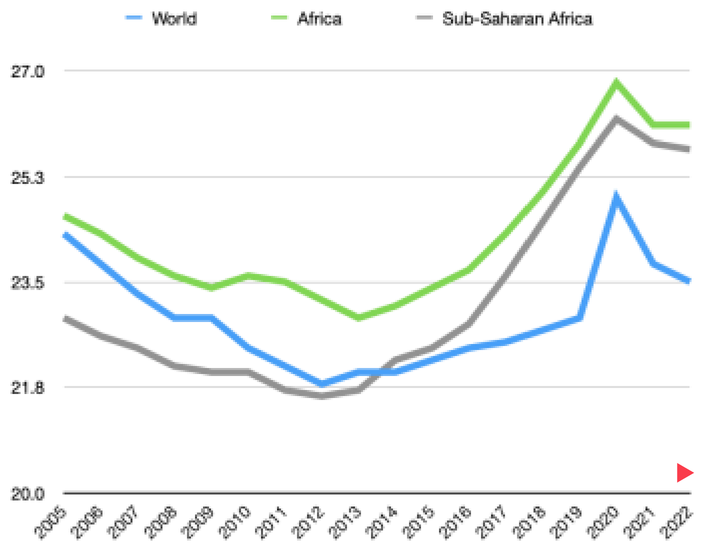


Challenges of moving up the (AI) value chain: Integrating the young labour force

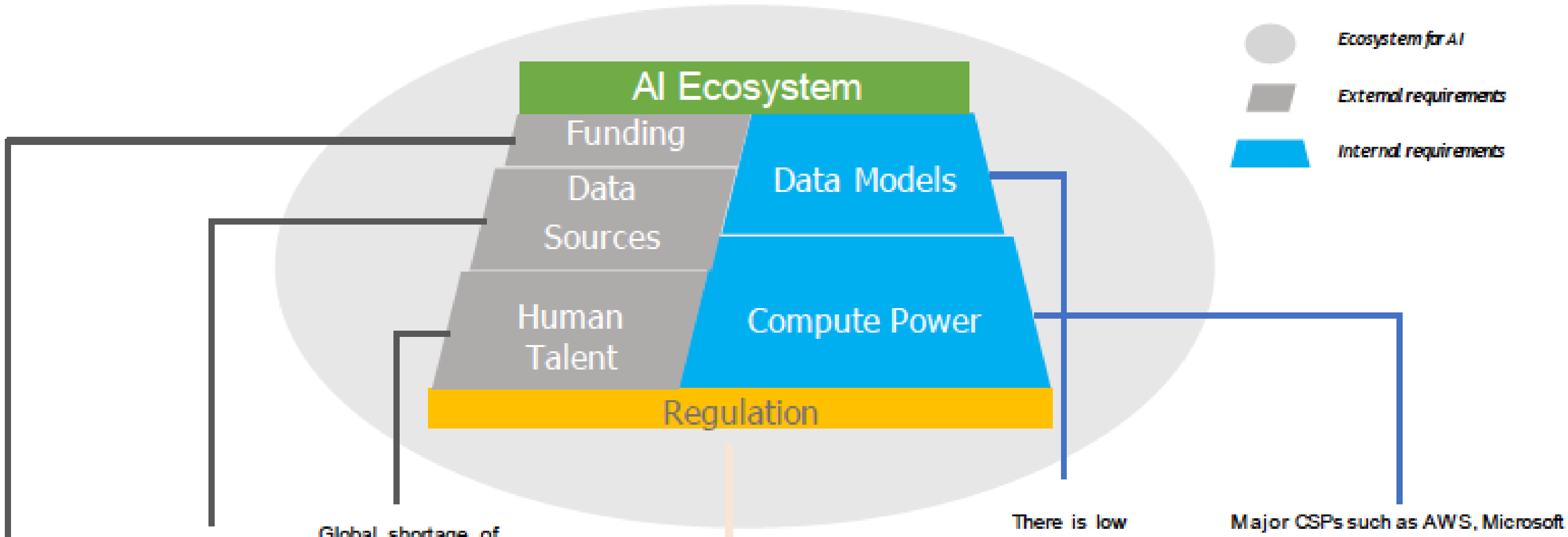
High youth unemployment/
NEET rates

Incomplete education, difficult school-to-work transition

Shortages of skilled labour in the Global North



Creating an AI eco-system…



AI startups are highly dependent on funding from Global North and Big Tech.

How can sources of funding be diversified?

Access to proprietary data is a key differentiator for training AI models, giving Big Tech a huge advantage.

How do we create publicly accessible open datasets that are representative of the population?

Global shortage of workers with skills and experience in deep learning, natural language processing and robotic process automation.

What initiatives are needed to ensure there is development and inflow human talent?

Varies highly across sectors and countries as states are unable to keep up with innovation.

What kind of standards and regulations are required for the development, benchmarking and use of AI solutions in a sector?

There is low prioritisation in developing large, diverse, and quality data sets to build AI models at scale in development contexts.

Are there existing frameworks to reduce error rates and biased outcomes in training?

Major CSPs such as AWS, Microsoft Azure, and Google Cloud dominate the market, collectively holding a 65 percent share globally. NVIDIA, a chip manufacturer, holds more than 90 percent of the market share for GPUs, the semiconductor chips essential for AI-related tasks.

How do you preserve sovereignty, maintain competition and prevent vendor lock-in?

…without compromising on AI regulation and governance

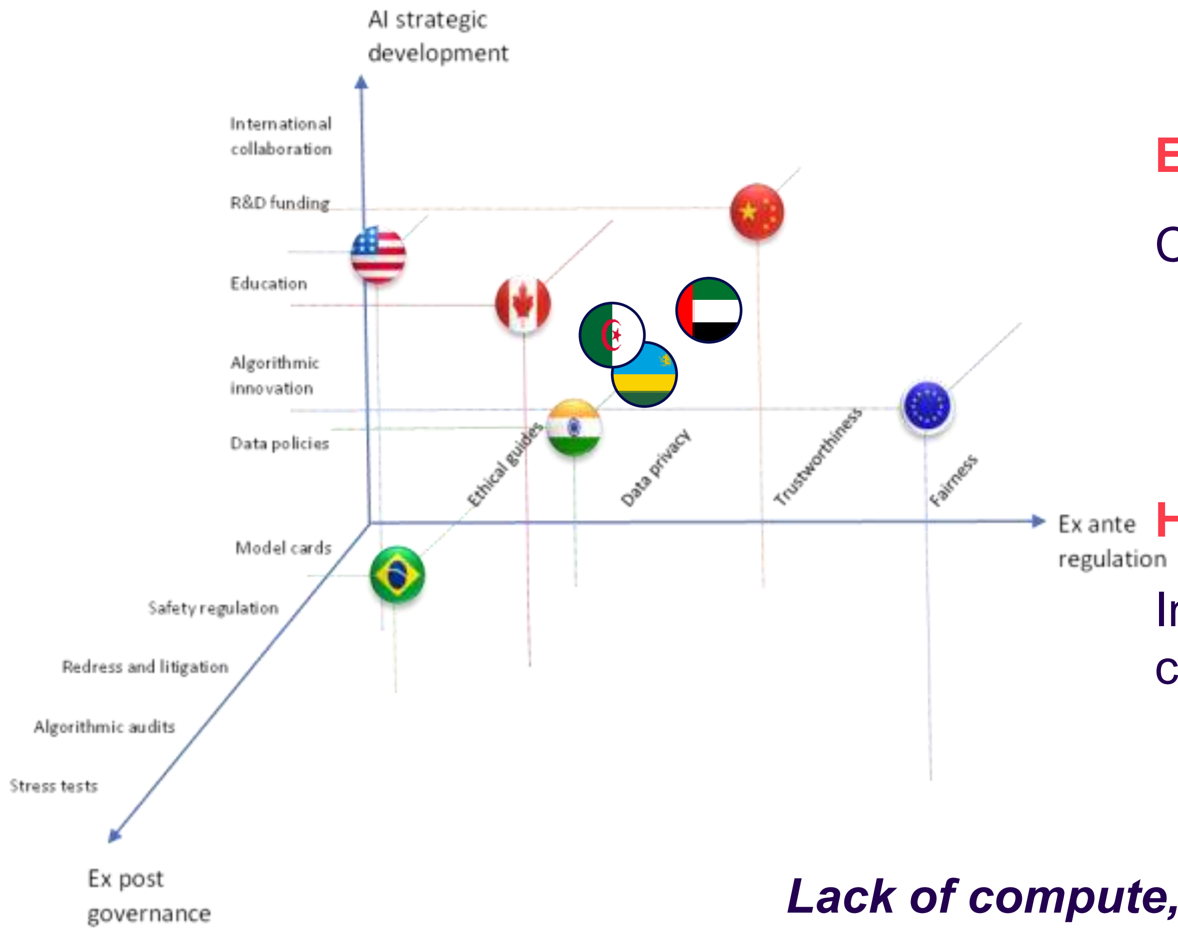
Strong focus on AI development:

USA, China, (Canada)

Algeria, Rwanda, UAE

Ex-post governance:

Canada, (Brazil)



Ex-ante regulation:

China, EU

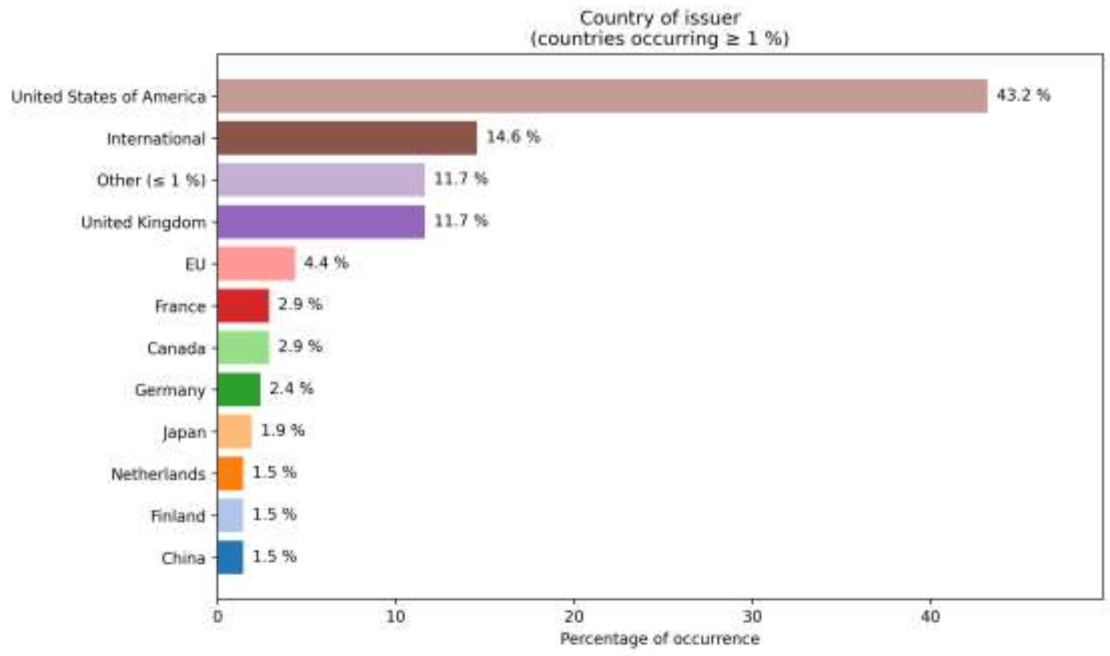
Hands-off approach:

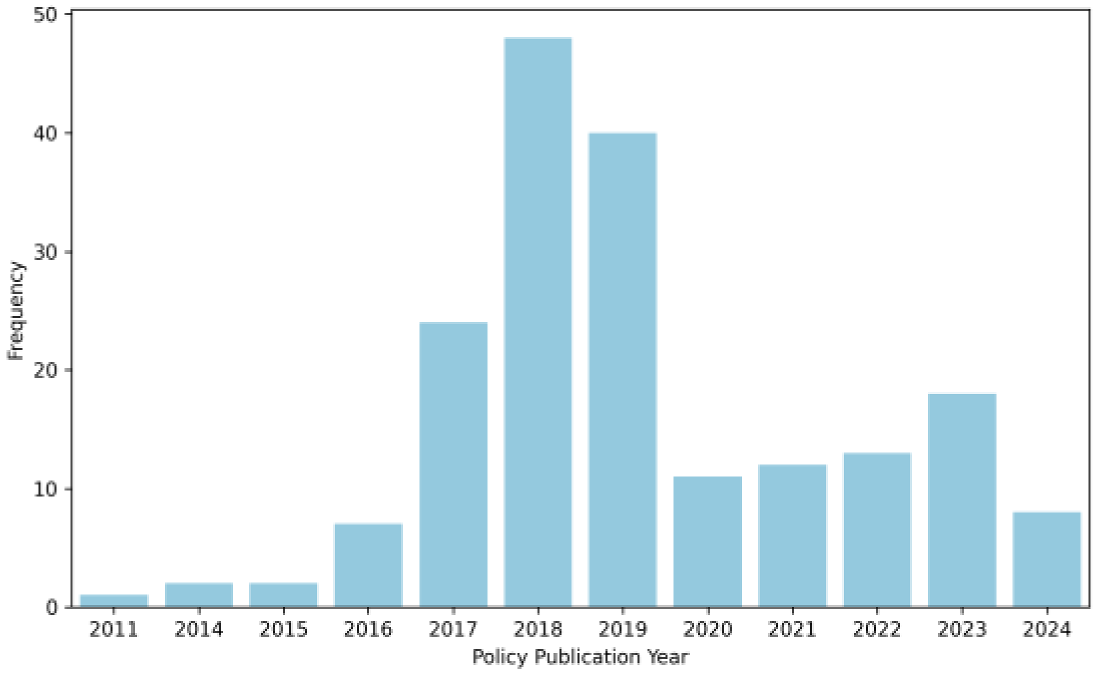
India, but with a protectionist component

Lack of compute, internet connectivity and human capital most pressing in the Global South

Governance standards dominated by the Global North…

…leaving countries in the Global South without a voice





Leapfrogging through AI

How can AI help countries in the Global South to leapfrog?

Help with policy delivery and monitoring	• Implementation of labour market policies and regulation • Improve trageting of marginalised groups (e.g. social security)
Manage complex networks	• Enhance the capacity of limited infrastructure capacity • Create new opportunities for trade
Enhance information provision	• Overcome informational barriers • Provide foresight tools
Share expertise	• Leverage scarce skills, new business creation

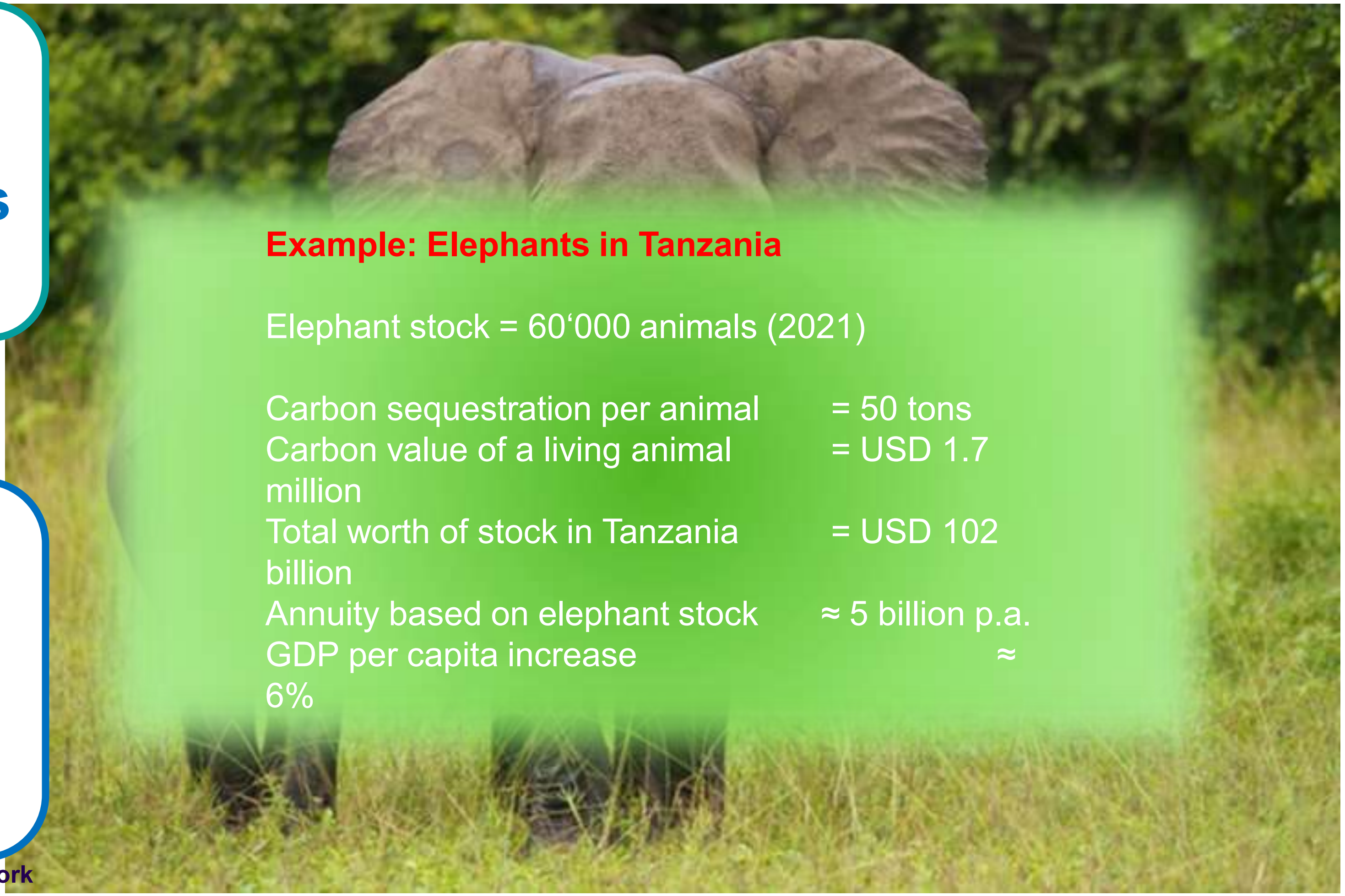
How AI and digitalisation can help countries to leapfrog

	Connectivity	Certification	Expertise	Solution for
Agriculture	Producers-markets	Agri-labels (blockchain)	Irrigation systems	Increase agricultural productivity/resilience
(Regional) trade	Foster trade (in services)	Facilitate market access	Trade negociations	Foster demand for (regional) production
Health care	Patients-doctors		Leverage scarce expertise	Underprovisioning of health care
Education	MOOCs	Micro-credentials	Trade in (skilled) services	Incomplete education/ Migration
(Youth) employment	Employers-youth	Policy delivery	Access to enterpreneurship	Local LM frictions
Smart cities	Smart mobility		Circular economy	Enhance infrastructure productivity
Renaturation	Carbon trading systems	Carbon credits		Lever for economic development and sustainability

Empower nature-based projects for local development

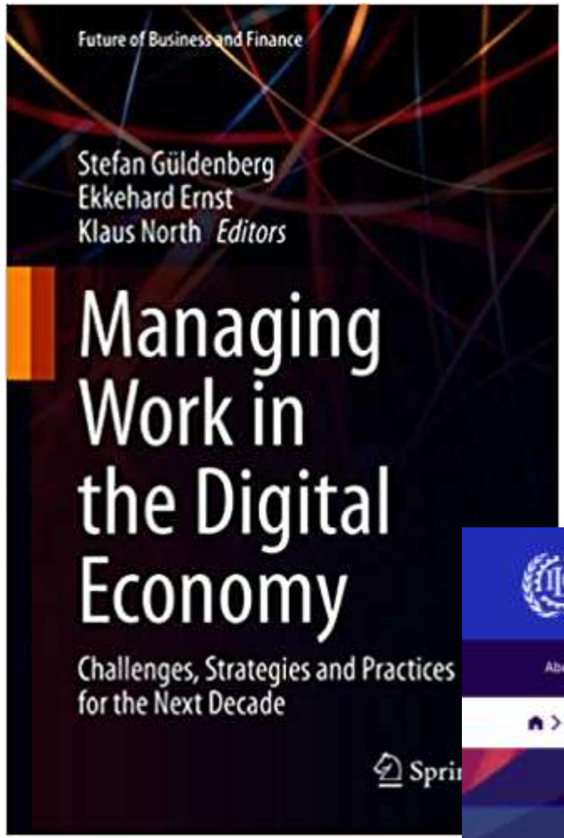
Creating digital twins

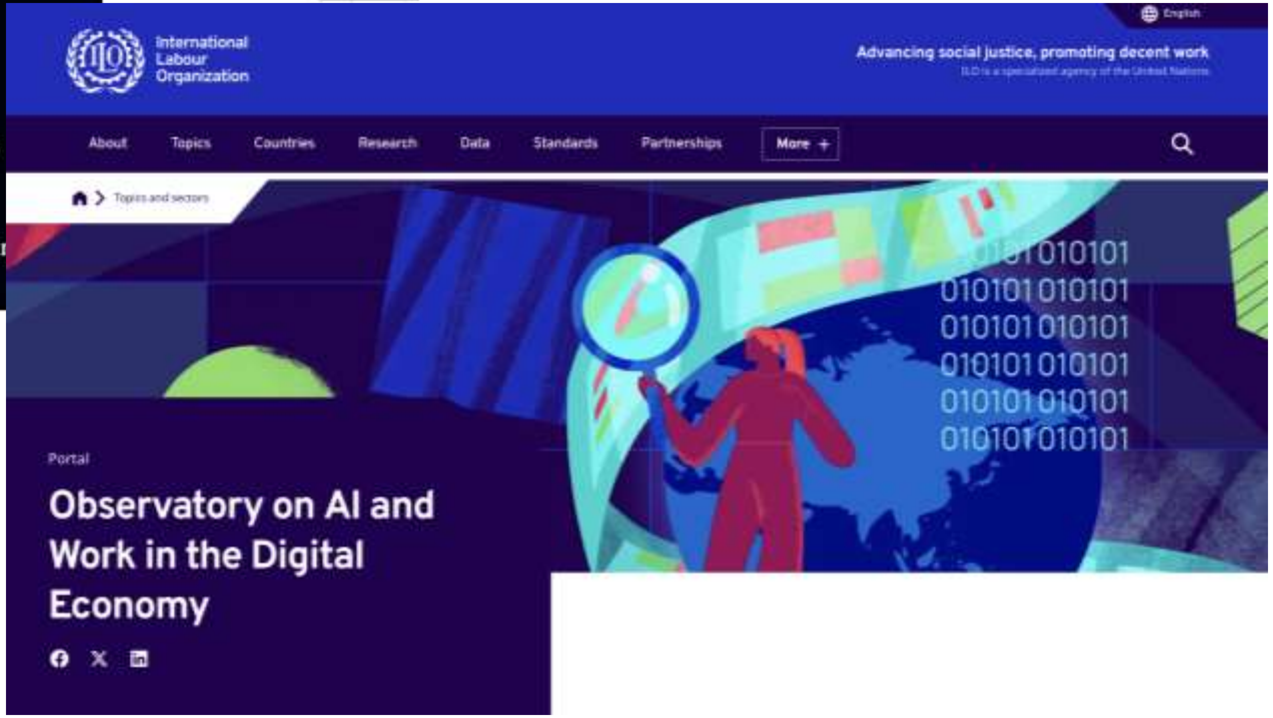
Payments for ecosystem services



International Labour Organization

Want to know more?





https://www.ilo.org/research-and-publications

https://www.ilo.org/topics-and-sectors/observatory-ai-and-work-digital-economy

International Labour Organization

Appendix

Technical details

How are these exposure measures constructed?

Expert insights: This method involves consulting experts to evaluate which tasks or occupations are susceptible to automation. Experts assess the tasks' potential for automation based on AI's capabilities. *e.g., Frey and Osborne (2013); Brynjolfsson et al. (2018) with crowd-based expert judgment; Felten et al. (2018, 2021, 2023)*

Patent data analysis: Using patent data to assess the impact of AI on labor markets by identifying automation-related technologies through textual analysis of patents and comparing them with job tasks. *e.g., Webb (2020); Dechezleprêtre et al. (2020); Gathmann and Grimm (2022); Mann and Püttmann (2023).*

AI-generated exposure measures: Leveraging generative AI models (e.g., ChatGPT) to assess the potential for task automation. These models evaluate tasks from databases like O*NET and ISCO to predict automation risk, both currently and in the future.
e.g., Eloundou et al. (2024); Gmyrek et al. (2023); Kogan et al. (2025); Chen et al. (2025)

Strengths and usefulness of AI exposure measures for policy makers:

- AI exposure measures provide a **risk-and-opportunity profile** for the labor market, based on potential adoption of AI in the near to medium term.

What is the magnitude of potential changes to my workforce in terms of:

- **Job transitions:** potential losses and creation of new jobs
- **Productivity gains** across occupations and sectors
- **Changing working conditions**
- **Income shifts** and distributional effects
- **Skills needs** and adjustments for workers
- They also help define **the policy space** — including potential regulatory changes.

Limitations:

1. Based on existing, unaltered work process and existing organizational structures:
Technologies are rarely targeted at replacing individual tasks; they often replace entire processes. In such cases, whether individual tasks are automatable or not becomes irrelevant.

2. Not linked to any (macro-) economic variables:
No theoretical connections are made to variables such as wages, profits, adjustment costs, prices, or productivity. The implicit assumption is usually a fixed-coefficient (Leontief) production framework.

3. Economic viability and probability of adoption not considered:
Neither economic factors (e.g., comparative advantages) nor contextual factors (e.g., legal, ethical, cultural, sociological) are taken into account. The result is a purely “technological feasibility” analysis.

4. Subjective measures:
They rely on experts’ opinions of what might be technologically possible now, in 5 years, or in 15 years. As AI evolves and experts revise their views, these measures change accordingly.

5. As a consequence of points 1–4: NO commonly accepted interpretation of meaning
Terms such as “suitability to machine learning,” “risk of automation,” “augmentation,” “replacement,” and “retraining” lack consistent, agreed-upon definitions.