

### New AI technologies, inequality, and inclusive growth

**Calvin Cheng** 

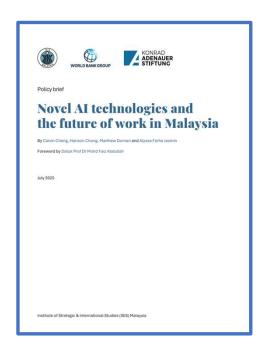
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#### **Report:**

#### Novel AI technologies and the future of work in Malaysia

Cheng, Chong, Dornan and Jasmin











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► New AI technologies can be a new risk for inclusive growth and inequality.

► Technology has continually shaped inequality and inclusion across human history – and novel AI technologies are the latest in this trajectory. Each wave of innovation has transformed who benefits, and who does not.



Source: Authors' illustrations. Chu et al. (2020), Frey (2024), Graetz and Micheals (2018), Katz and Goldin (2007), Autor (2020). Acemoglu (2022), Bastani (2019) ► Technological change since the 1980s onwards have increased inequality. Research suggests that computerisation and industrial robots have contributed to a global decline in labour share of income, fuelled inequality, and gave rise to political polarisation.

► Generative AI impacts are wide-ranging globally.

► Up to 40% of jobs globally already highly exposed to current Generative AI technologies

Job exposure to AI (% of jobs) by region, empirical estimates

**Developed** economies

**^^^** 

4 in 10 workers highly exposed to AI

**Emerging** economies

**††**†ůůůůůůůůů

2 in 10 workers highly exposed to AI

Source: Pizzinelli (2023); Talentcorp (2024).



Note: Developed economies = United States and United Kingdom. Emerging economies = Brazil, South Africa, and Colombia. Highly exposed = in top 20<sup>th</sup> percentile of AI exposure.

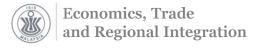
\*Only for 10 sectors, includes exposure to green economy and digital technologies.

## ► 28% of the Malaysian workforce are highly exposed to generative AI.

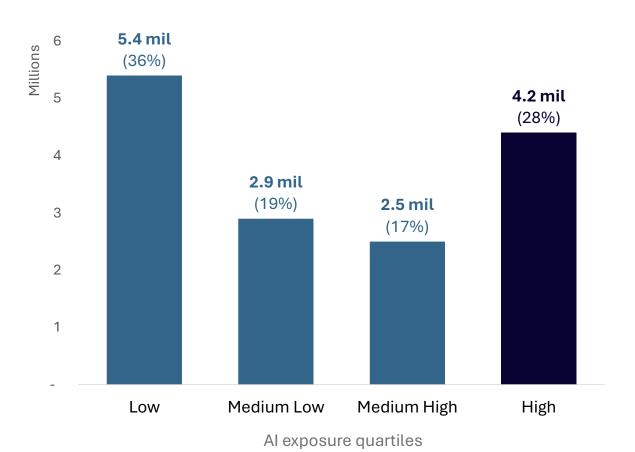


Source: Cheng et al. (2025). Authors' calculations based on DOSM data.

Note: Percentages = share of workers in the category of Al exposure as a percentage of all workers.



Employed persons by quartiles of AI exposure (2021), millions

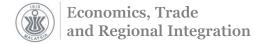


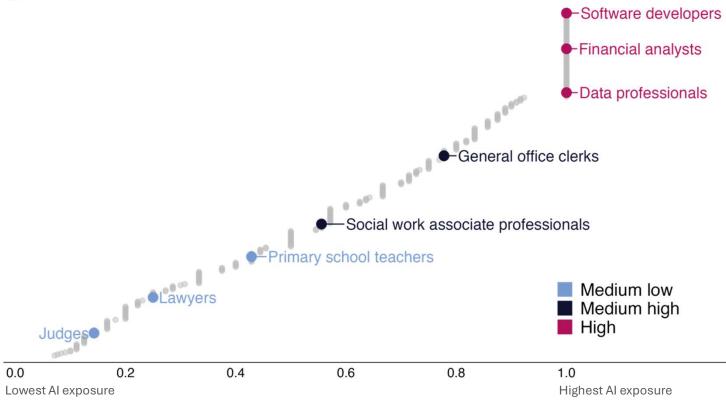
### ► Some jobs are most exposed to Al than others.

Occupations ranked by AI exposure (0 = least exposed, 1= most exposed)



Source: Cheng et al. (2025). Authors' calculations based on e-MASCO data. Note: Analysis of 484 jobs at the 4-digit level.

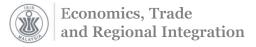




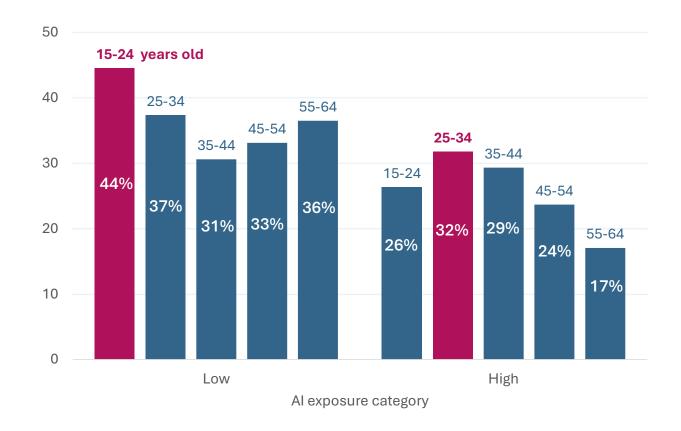
► Younger prime-age and early career workers are more exposed to generative AI.



Source: Cheng et al. (2025). Authors' estimates based on Labour Force Survey data.



Share of employment (%) in the highest and lowest quartiles of AI exposure, by age group



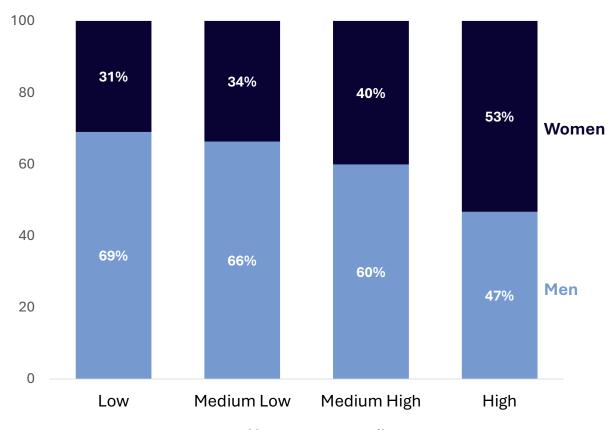
➤ Women nearly
2x more likely to be
'highly exposed' to
generative AI than
men.



Source: Cheng et al. (2025). Authors' estimates based on Labour Force Survey data.



Share of employment (%) by quartiles of AI exposure, by gender



Al exposure quartiles

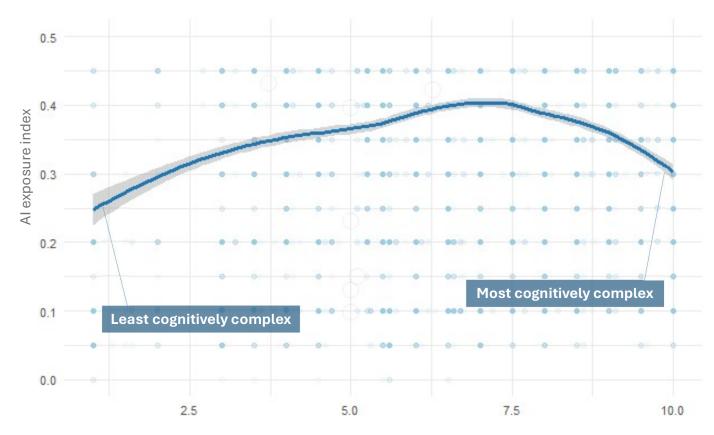
#### ► Hollowing out the middle (1):

Al automation exposure **peaks in the middle** –
and plateaus at highest-cognitive tasks.

Source: Cheng and Chong (2025).



Skill-wages and average AI exposure index, scatter plot and fitted line



Cognitive complexity score (higher = more complex)

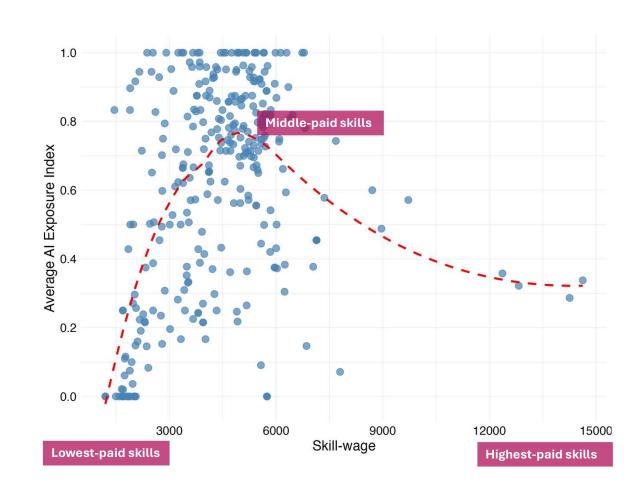
### ► Hollowing out the middle (2):

Skills in the "middle" are most automatable by generative AI.

Source: Cheng et al. (2025). Note: Red line estimated via LOESS (local) regression.

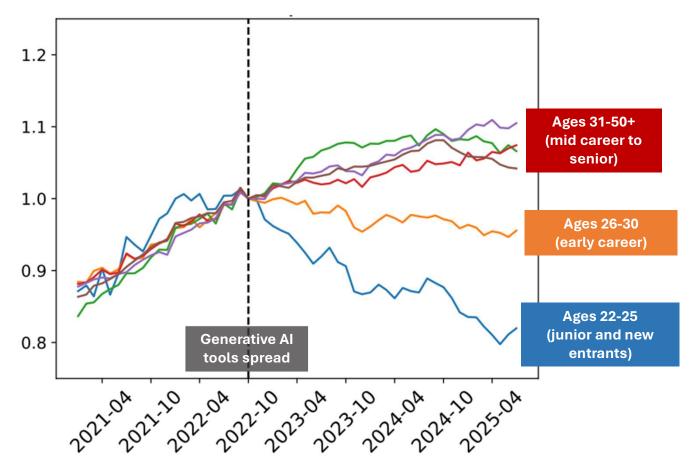


Skill-wages and average AI exposure index, scatter plot and fitted line



New data from the US: early career workers in AI-exposed occupations saw 13% decline in employment.

Employed by age group (2021 to 2025), software developers in the US



Source: Brynjolfsson, Chandar, and Chen (2025). Based on US data.



17%

7%

► Al exposure varies widely across countries in the region.

28%

33% 36% 35% 34% 69%

38%

**SGP** 

Al exposure quartiles, exposure as % of total employed

38%

USA

32%

MYS

4%

6%

**MMR** 

Medium low

Medium high

■ High

Low

11%
14%
14%
12%
10%
58%
45%

39%

AUS/NZL

39%

PHL

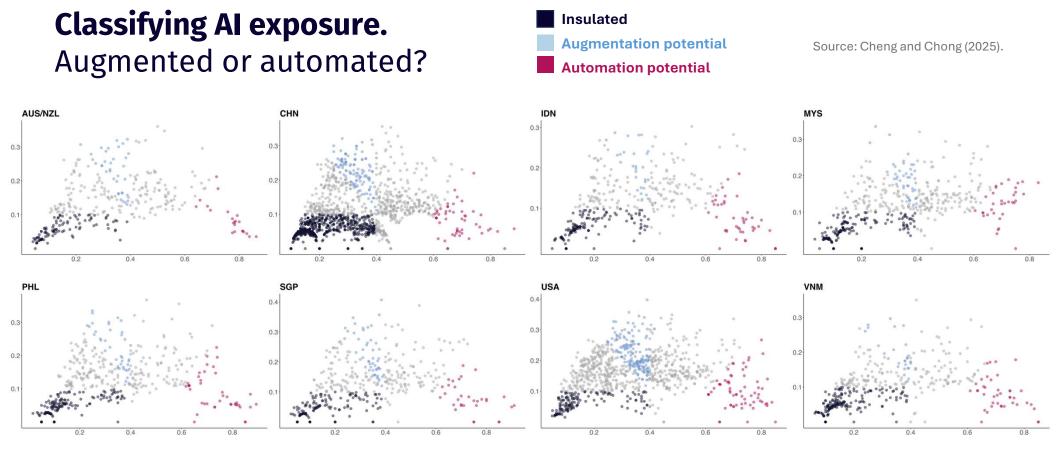
IDN

Source: Cheng and Chong (forthcoming, 2025).



CHN

**VNM** 

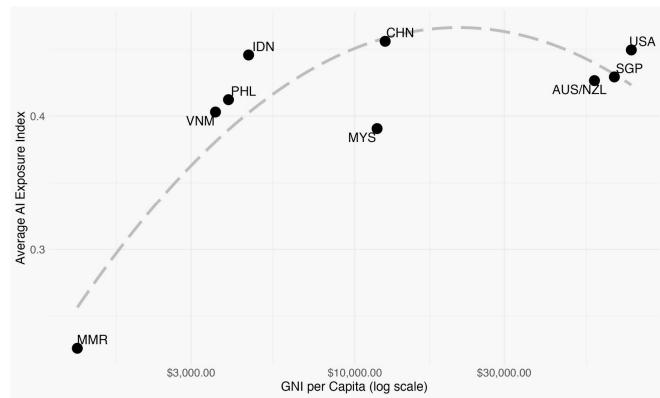


Note: Figures for Myanmar are unavailable because Myanmar's figures are obtained at the occupational level. Dark blue indicates occupations that are classified as "insulated", dark pink indicates occupations that have "automation" potential, light blue indicates occupations that have "augmentation" potential, and grey indicates occupations classified as "mixed".

#### Middle-income economies have highest "automation" exposure to generative Al...

#### Middle-income countries may face the largest automation risk.

Automation % of jobs, by country



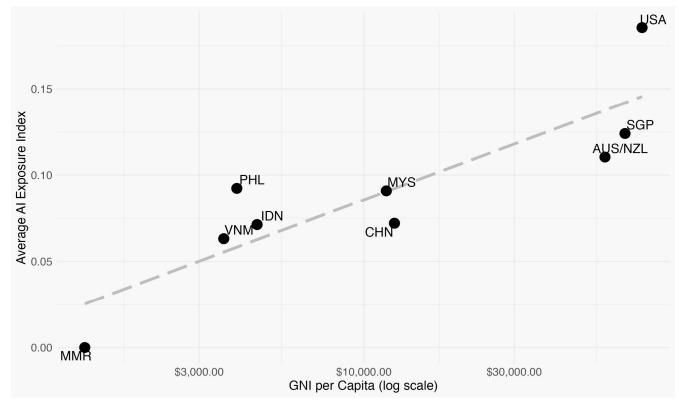
Source: Cheng and Chong (forthcoming, 2025).



#### ...while advanced economies have the highest augmentation potential.

#### Richer countries enjoy greater augmentation potential from AI.

Augmentation % of jobs, by country



Source: Cheng and Chong (forthcoming, 2025).



#### **Takeaway:**

New AI technologies may increase within-country inequality.

Read more here



Source: Cheng et al. (2025).



- ► New AI technologies are now widespread, and create new challenges for inequality and inclusive growth.
- ▶ Our estimates show AI exposure is unequal across gender and age. Women and younger workers are amongst the most exposed to AI technologies.
- ► Generative AI could deepen job polarisation by hollowing out the middle. Extends inequality impacts from past waves of technology.
- ▶ Occupations that emphasise "human edge" skills may become more valuable as generative AI automation progresses.

#### **Takeaway:**

New AI technologies may also increase between-country inequality and threaten developmental pathways.

- ► Relatively high AI exposure overall, but wide disparities between countries
- ▶ Middle income squeeze. Automation risk peaks in middleincome economies, while augmentation benefits accrue disproportionately to advanced, high-income economies.
- ▶ Developmental pathways at risk: traditional services-led convergence could stall as developing economies face higher automation of jobs (automation of tradeable services), while advanced economies capture unequal "Al dividends" through augmentation.

Source: Cheng et al. (2025).

### What can individual countries do?

- ▶ **Social protection.** Extend social protection coverage to all workers across the life-cycle. Universal access to lifelong learning.
- ▶ Education and training. Mainstream AI education while cultivating "human edge" skills like social intelligence, and implementing flexible credential pathways.
- ▶ Labour market institutions. Make it cheaper for firms to invest in workers' skills and raise job quality through stronger worker bargaining power. Universal labour guarantee.

Source: Cheng and Chong (2025).



## What can countries in the region do together?

- ▶ Rebuilding regional agency. Restoring collective agency through strengthening and modernising domestic labour market institutions. ASEAN-level: common labour and digital standards, pooling of funds to develop homegrown AI technologies.
- ▶ Remaking market incentives. Realigning the underlying incentive structures that underpin technological development and adoption towards progress over profit. Fiscal tools, open-source mandates, collective ownership.

Source: Cheng and Chong (2025).



## What can donor institutions and development partners do?

- ► Helping recipient countries strengthen labour standards and governance. Embed labour and digital standards, skills recognition, and social protection portability into trade arrangements along with capacity-building/support.
- ▶ Share experience in building adaptive skills training and lifelong learning systems. Co-finance lifelong learning, labour market governance, and universal social protection, while building domestic revenue and subnational (federal) capacity so reforms are fiscally sustainable.
- ▶ Strengthen regional agency for shared standards, rules and co-innovation. Finance norm-setting, mutual recognition frameworks, and pooled funds for home-grown AI and digital public goods. Convene governments, firms, and workers to co-design rules.

Source: Cheng and Chong (2025).





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