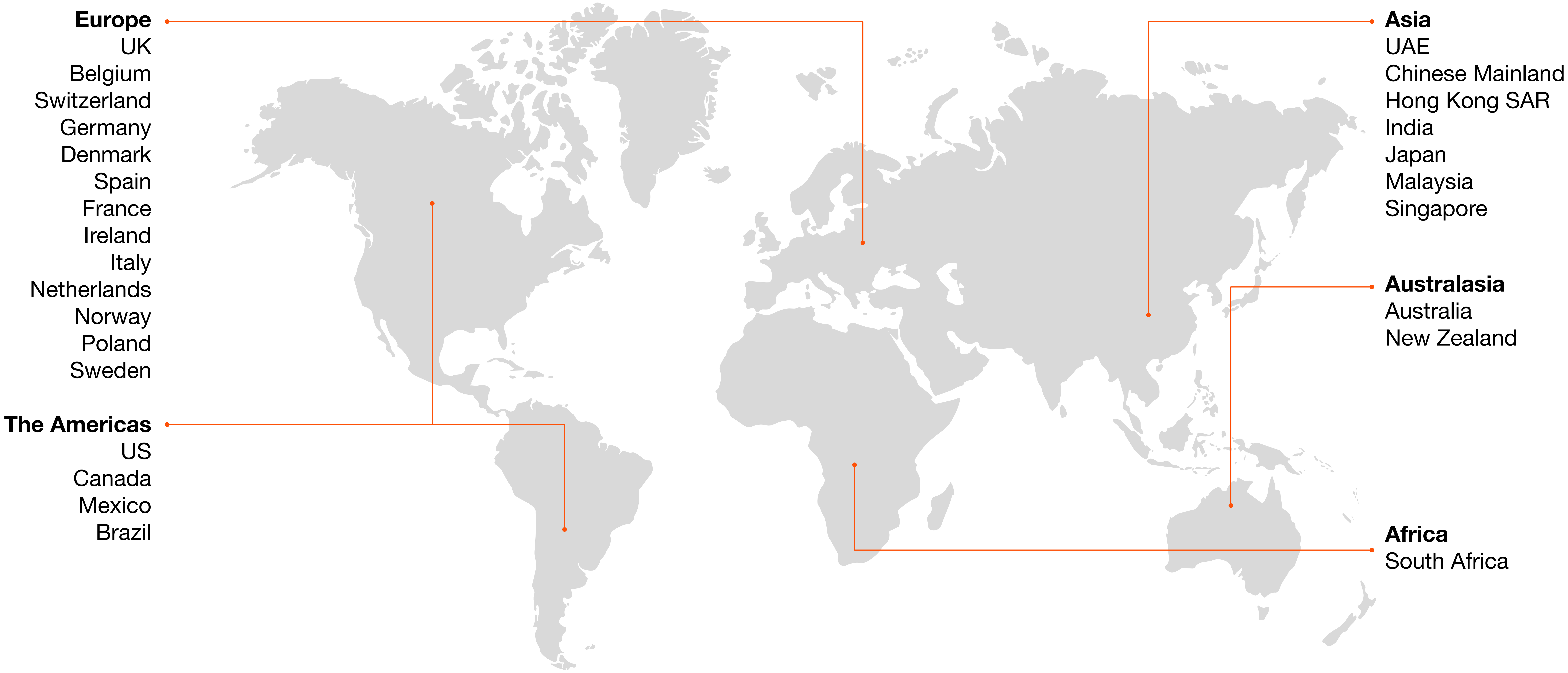
Two futures for jobs in an AI era

2026 Global AI Jobs Barometer

The 2026 AI Jobs Barometer examines over one billion job ads from 6 continents to reveal how AI is affecting jobs, skills, wages, and labour productivity



Appendix 1 – Methodology

Appendix 1a:

PwC AI Occupational Exposure (AIOE) Index

We have refreshed Felten’s original AIOE Index to capture the evolution of work and advancements in AI capability since 2018-19

The original AIOE reflected the world as it stood in 2018-19. But since then, things have changed:

1. **Workforce composition has evolved:** new digital, data-driven and hybrid occupations have emerged, while others have declined or changed skill profiles

2. **AI capability has advanced:** LLMs, multimodal systems and GenAI now perform a wider range of cognitive and creative tasks than the models considered in 2018

To keep the index accurate to today’s labour market, **we refresh it to reflect both the new occupational landscape and the expanded reach of modern AI**

We follow Felten’s original methodology step-by-step, ensuring continuity while incorporating the latest data:

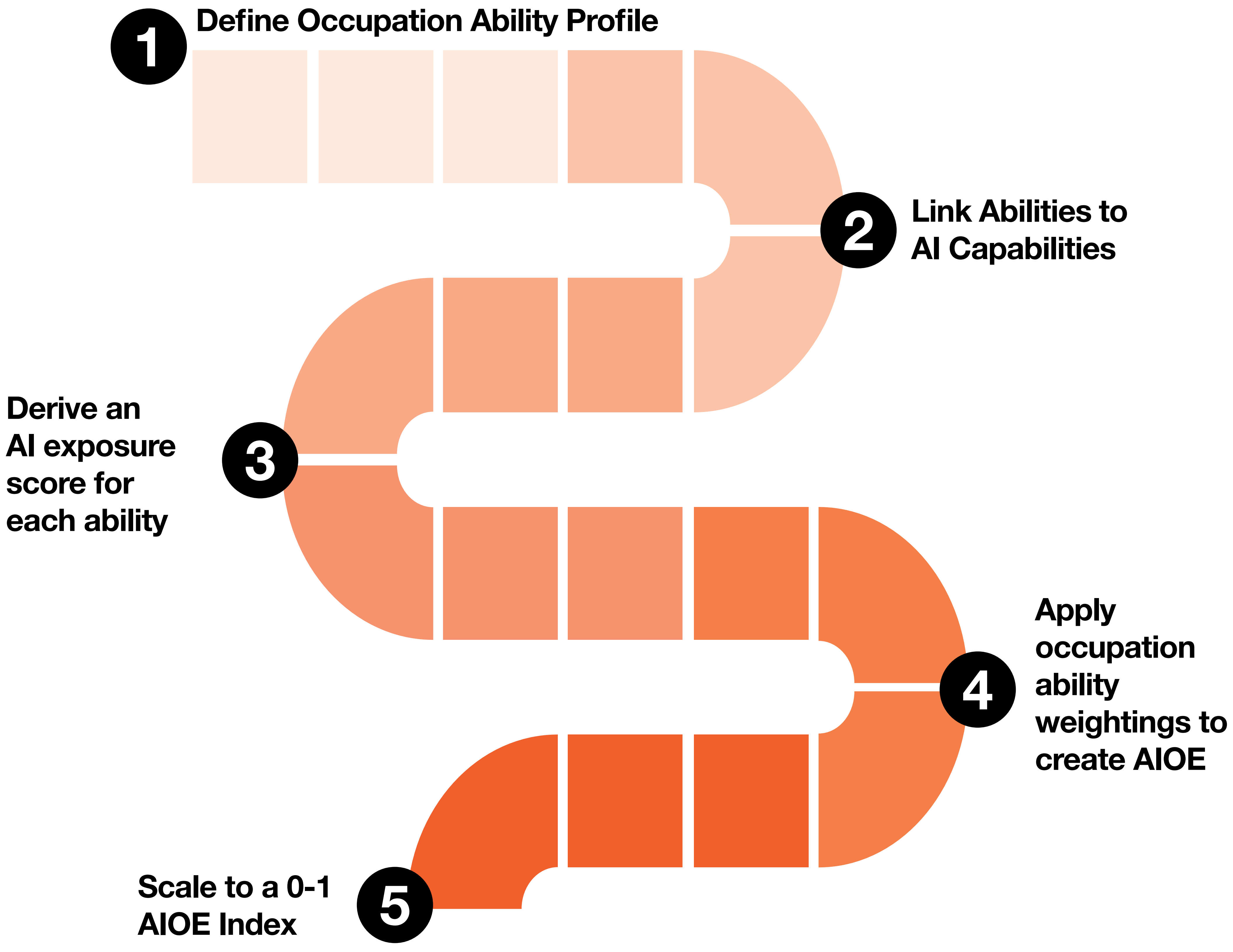
We update the O*NET Abilities dataset to capture new occupations and revised ability weights

We refresh the AI-Ability matrix by leveraging the expertise of SMEs from the PwC Data & AI team to better represent how today’s AI systems relate to each ability

We re-calculate AIOE scores using the same aggregating process as Felten, producing a comparable, up-to-date measure

This enables us to calculate updated AI Occupation Exposure scores, following Felten's five-step process for each occupation…

Five-step process to develop an AI Occupation Exposure Index:



Illustrative Example: Step-by-Step AIOE Construction for Lawyers

1. **Define a Lawyer's ability profile using O*NET**
Lawyers rely heavily on communication and reasoning abilities, with oral expression, written comprehension, and deductive reasoning identified as the most important abilities.

2. **Assess the capability of 10 AI applications to conduct 52 O*NET abilities**
Agnostic to any specific occupation, we create a relationship matrix analysing the capability of the major AI tools to conduct different human abilities.

3. **Create an ability exposure score by aggregate the 10 AI applications capability to conduct each ability**
We aggregate the occupation agnostic relationship matrix to calculate an exposure score for each ability.

4. **Calculate the AI exposure score for a Lawyer**
We apply the ability exposure scores to the Lawyers ability profile, weighting each of the abilities exposure scores by the importance and level of the ability for each occupation.

5. **Scale to a 0-1 AIOE Index score**
The result is a raw AIOE of 6.85, which after scaling between 0-1 yields an AIOE of 0.974, placing Lawyers among the most AI-exposed occupations in our dataset.

Appendix 1b:
PwC AI Industry Exposure (AIIE) Index

Building the PwC AI Industry Exposure Index

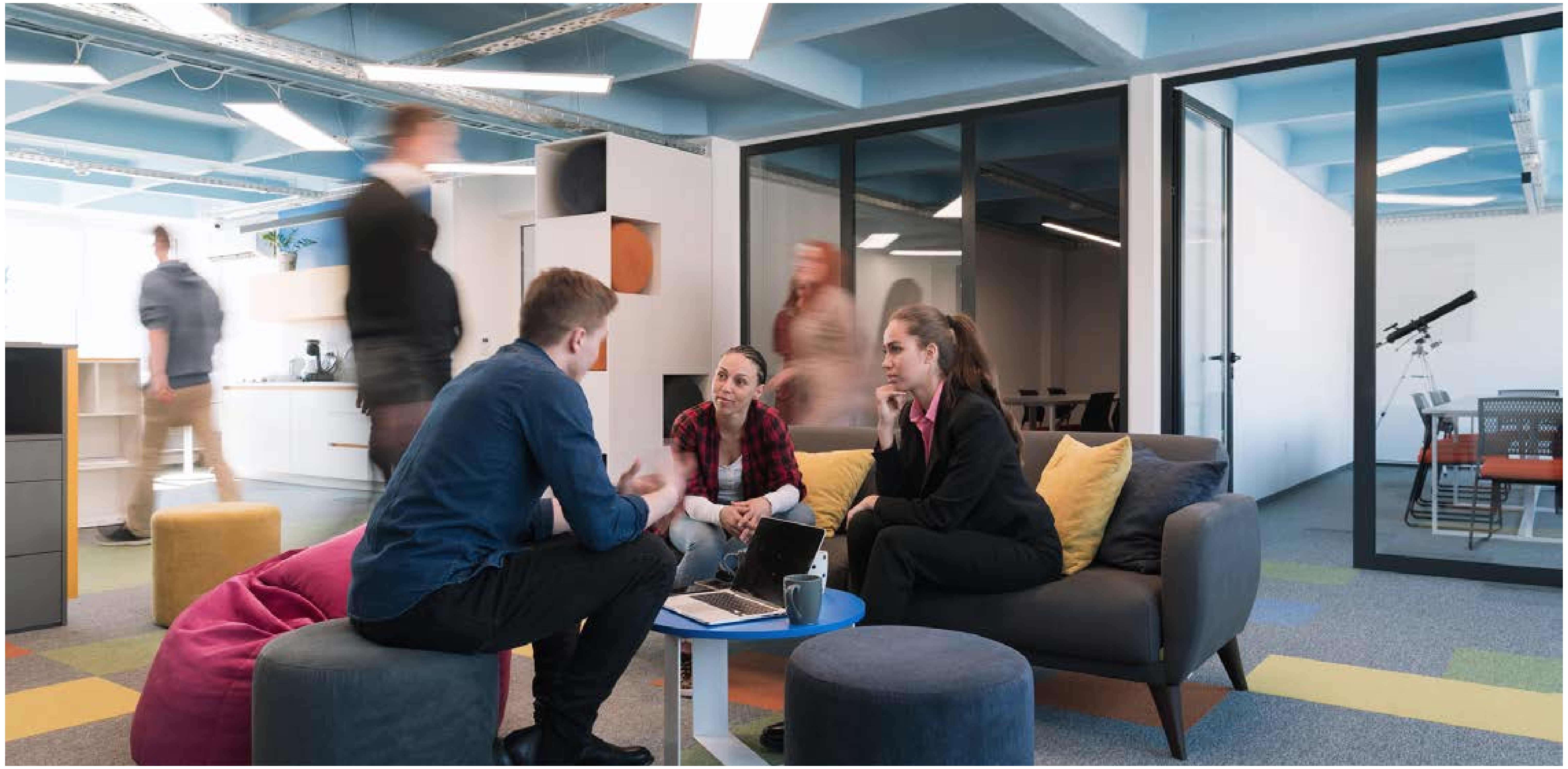
The PwC AI Industry Exposure Index builds on Felten et al. (2021)'s AI Industry Exposure framework, which measures how exposed industries are to AI based on the relationship between occupational requirements and AI capabilities. Felten's original industry index was produced at NAICS level using US occupation-by-industry employment data. PwC adapted this approach to create a sector exposure index aligned to UK SIC07 industries, consistent with the sector structure used in the AI Jobs Barometer.

At a high level, the index combines:

- **Occupation-level AI exposure:** Updated occupation-level AI exposure scores, reflecting how exposed different occupations are to AI capabilities.
- **Sector employment mix:** UK employment data showing the occupational composition of each sector.
- **Employment-weighted sector scores:** Each sector's AI exposure score is calculated from the share of employment in AI-exposed occupations. Sectors with more employment concentrated in AI-exposed occupations receive higher scores.

The final index allows us to compare the relative AI exposure of sectors on a consistent basis and group sectors by exposure level for further analysis.

Important interpretation: a higher exposure score does not imply job loss or automation. It means a sector has a greater share of work in occupations where AI capabilities are relevant and therefore may experience greater task-level transformation.



Appendix 1c:

Net Skill Change Methodology

How we calculate net skill change

The net skill change is a measure of the change in the frequency of skills required by employers for a particular occupation. This metric and its associated methodology to be calculated was developed by Harvard economists, David Deming and Kadeem Noray (2020).

Below we present the formula and walk through an example.

In short, the net skill change takes the absolute value of each skill change for an occupation and sums them. As it measures the absolute value the value is always positive.

It is capturing skill changes be they positive or negative and adding them. The more changes in skills demanded by an employer be they demanded more or less (positive or negative), the higher this net skill change value.

Example:

If skill A is mentioned 50 times in 2019 and then 65 times in 2023 (and we assume job postings remained constant in both time periods at 100 for example). The skill change would be 65/100 - 50/100 = 15/100 = **+0.15.**

If skill B is mentioned 30 times in 2019 and then 25 in 2023 (in 100 postings in both periods), the skill change would be 25/100 - 30/100 = -5/100 = **-0.05.**

The net skill change the sum of the absolute values:

Net skill change for job X = 0.15 + 0.05 = **0.20.**

Formula:

$$Net\ Skill\ Change_{0,t2,t1} = \sum_{s=1}^{S} Abs\left[\left(\frac{Skills^{s}_{0,t2}}{JobAds_{0,t2}}\right) - \left(\frac{Skills^{s}_{0,t1}}{JobAds_{0,t1}}\right)\right]$$

Appendix 1d:

Productivity Analysis Methodology

Our productivity analysis includes a range of metrics and our methodology for each metric is outlined below

#	Metric	Data	Methodology
1	AI exposure vs growth rate in productivity by sector	PwC AIIE Index Orbis: Growth rate in TPE	Turnover per employee is calculated by dividing operational revenue by headcount. At firm level we calculate average TPE for both the top and bottom quartiles of AI exposure by dividing the sum of operational revenue across all firms in that quartile of exposure by the sum of employment across all firms in that quartile of exposure. The percentage change across the 2018 and 2024/25 values is then taken as the growth rate.
2	AI exposure vs growth rate in headcount by sector	PwC AIIE Index Orbis: Growth rate in headcount	Headcount is directly provided in the Orbis data as 'EMPL'. The percentage change across the 2018 and 2024/25 values is then taken as the growth rate. To calculate the average EMPL growth for both the top and bottom quartiles of AI exposure we sum the headcount of all firms in that quartile of exposure and compare the 2018 result to the 2024/25 result.
3	AI exposure vs growth rate in wage per employee by sector	PwC AIIE Index Orbis: Growth rate in wage per employee	Wage per employee is calculated by dividing total staff costs by headcount. At firm level we calculate average WPE for both the top and bottom quartiles of AI exposure by dividing the sum of staffing costs across all firms in that quartile of exposure by the sum of employment across all firms in that quartile of exposure. The percentage change across the 2018 and 2024/25 values is then taken as the growth rate.

Note: AI Exposure

All three metrics are examined against **AI Industry Exposure** values from the PwC AI Industry Exposure Index. This ultimately allows us to assess the impact of AI exposure on productivity, headcount, and wages at firm level. The AI Exposure of a firm is taken to be the AI Industry Exposure score of the NAICS 2022 sector that company is tagged to in the ORBIS data.

Note: 'Superstar' Companies

Our calculations for the 'superstar' companies involve zooming in on the companies that sit in the top quartile of AI exposure. From there, we sort these companies from largest to smallest by their TPE growth rates and then extract the average TPE/EMPL/WPE growth figures for the top 20% of companies in this quartile (top quintile within the top quartile of AI exposure).

In arriving at our final datasets, we apply a series of assumptions and filters that impact the overall firm count

#	Filter	Rationale	Number of firms removed	Number of surviving firms
0	Orbis Raw Data (pre-filtered for firms with $50mn+ OPRE)	This is the starting dataset	N/A	144,524
1	Removal of all entries with fewer than 4-digit/NA/empty NAICS codes	We clean the Orbis dataset and remove any NAICS code entries that are empty/NA or are not 4 digits long	1,893	142,631
2	Removal of entries that have a 4-digit NAICS code with no direct match in the PwC AIIE Index	We are unable to tag these firms to a corresponding sector-specific AI exposure value	41,096	101,535
3	Removal of entries with empty/NA operating revenue and headcount values in 2018 and 2024/25	We are unable to calculate gains for firms that are missing headcount and turnover data for 2018 and/or 2024/25	47,780	53,755
4	Removal of firms that do not have 10 or more employees in 2018 and 2024/25	We deem 10 employees to be a reasonable threshold for a firm to be considered 'normal'	1,447	52,308
5	Removal of firms that have 0 or negative operational revenue in either 2018 or 2024/25	Operational revenue of 0 or negative is unrealistic in the context of our analysis and we treat these entries as anomalies in the data	34	52,274
6	Limiting extreme productivity values from outlier firms via winsorization (set to 98%)	We use winsorization as an outlier treatment technique to limit anomalies and extreme values in our dataset. We reset all productivity growth values that fall below the 1st percentile and above the 99th percentile to the 1st and 99th percentile values.	0	**52,274 (TPE/Headcount Table)**
7	Removal of firms that have 0/NA/negative STAFF costs in either 2018 or 2024/25	Negative staff costs and staff costs of 0 are unrealistic and would cause a calculation error when computing 'wage per employee'	N/A (Parallel Table)	39,110
8	Removal of firms that have a 'wage per employee' value that falls outside of $1000 - $10,000,000	We filter out the possibility of negative wages and leave the upper bound relatively open, considering other filters are already in place	149	**38,961 (Wage Table)**

Other Filters

We apply the wage filters (7 and 8) last, as applying these filters before the productivity and headcount analysis results in a substantially smaller dataset for the productivity and headcount analysis. As such, we duplicate a parallel dataset to be used separately for the wage analysis. We apply filters 7-8 on the wage table.

Appendix 1e:
Data Availability

We analyse over 1 billion job advertisements globally

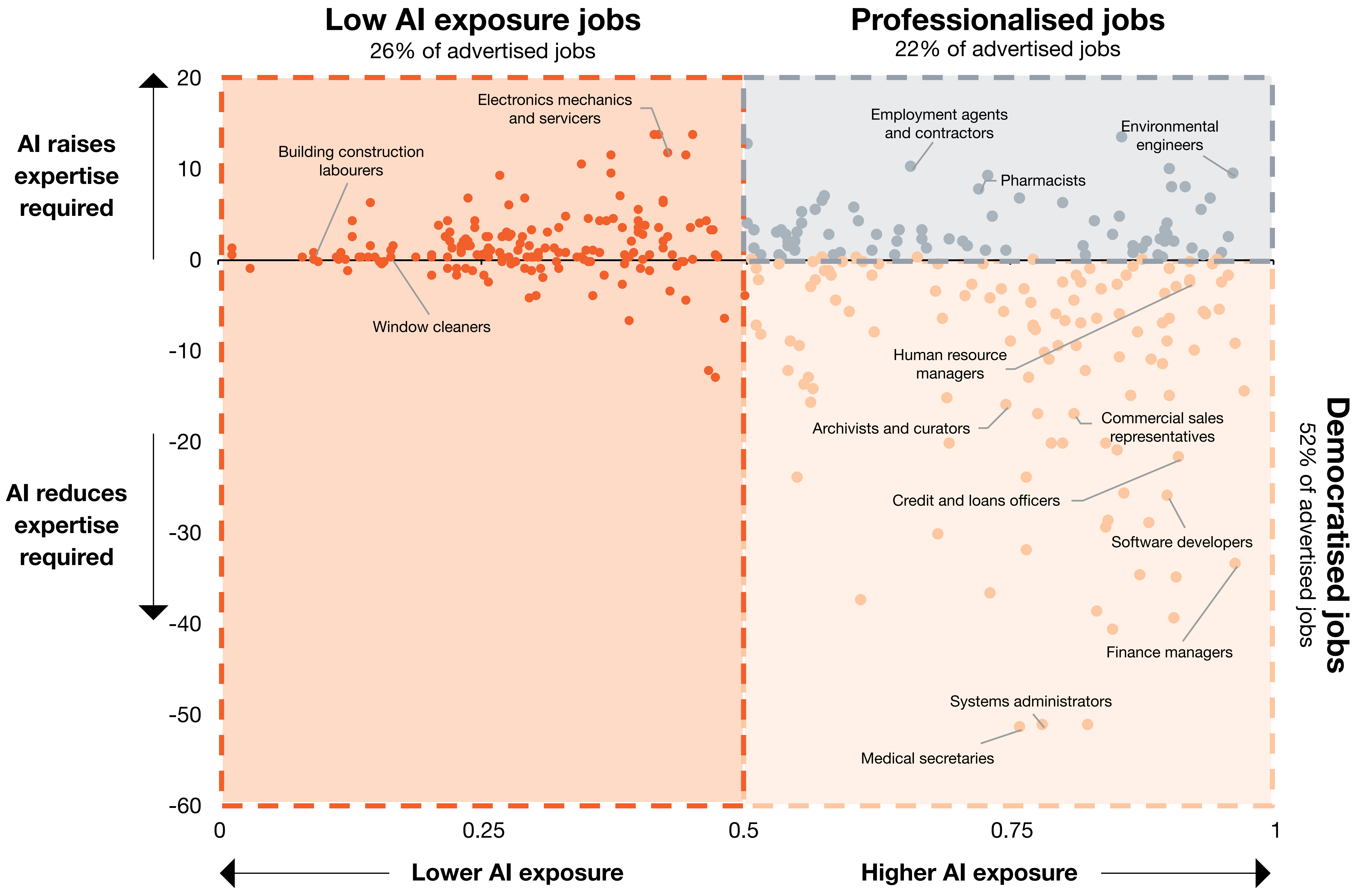
Countries included in the analysis and the number of postings analysed for each country

#	Country	Number of postings
1	Australia	**15.9 m**
2	Canada	**27.2 m**
3	United Kingdom	**121.8 m**
4	New Zealand	**3.7 m**
5	Singapore	**15.7 m**
6	United States	**449.1 m**
7	Belgium	**15.7 m**
8	Switzerland	**8.7 m**
9	Chinese Mainland	**86.5 m**
10	Germany	**82.6 m**
11	Denmark	**4.3 m**
12	Spain	**14.2 m**
13	France	**79.4 m**
14	Ireland	**4.8 m**

#	Country	Number of postings
15	Italy	**18.4 m**
16	Netherlands	**17.5 m**
17	Poland	**13.4 m**
18	Sweden	**10.5 m**
19	United Arab Emirates	**2.5 m**
20	Brazil	**21.1 m**
21	Hong Kong SAR	**2.8 m**
22	India	**30.2m**
23	Japan	**11.2 m**
24	Mexico	**19.3 m**
25	Malaysia	**6.6 m**
26	Norway	**2.2 m**
27	South Africa	**3.9 m**

Appendix 1f:
Additional Data

AI's impact on expertise is especially strong for Democratised jobs



Of 380 ISCO-08 job categories, 74 are Professionalised, 125 are Democratised, and 181 have low exposure to AI. 40 SOC-2018 occupations are excluded from the analysis because of limited data quality from Teeselink et al. for ranking expertise.

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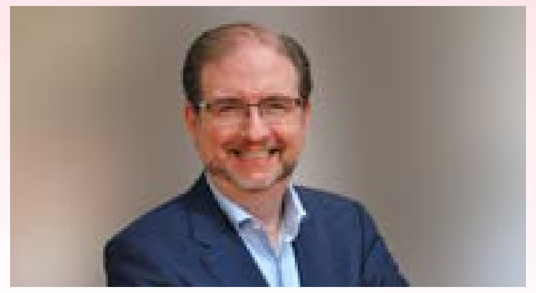

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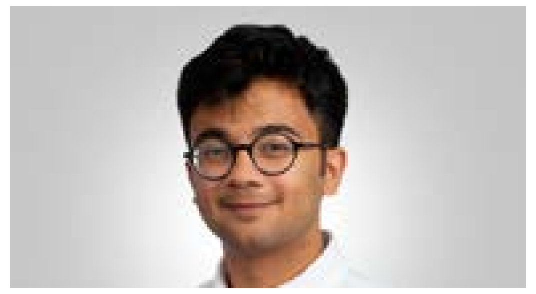

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