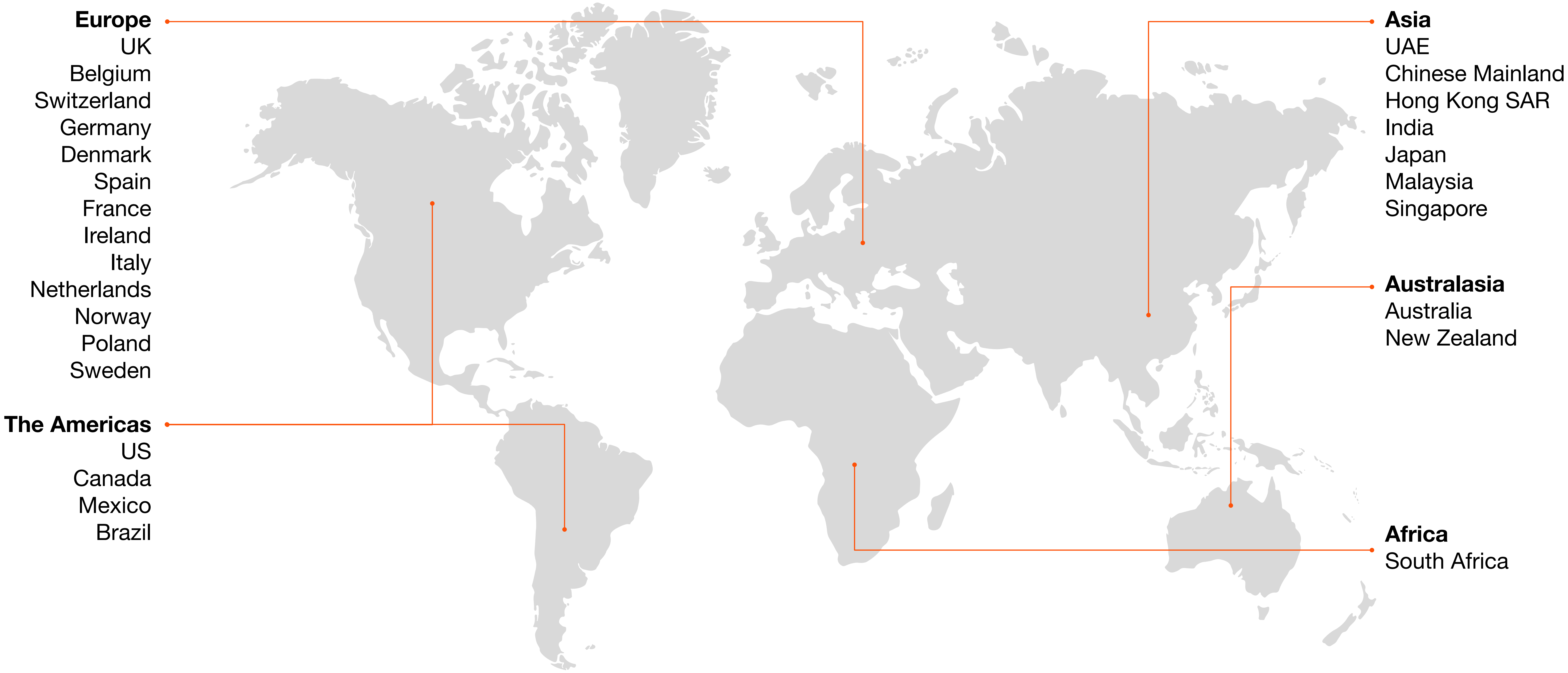
Two futures for jobs in an AI era

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



Executive summary

Key findings

AI is driving productivity, accelerating skills change and starting to create a redesign of entry level work

AI is strongly linked to significant productivity gains

Since 2022 when AI use soared, companies in the sectors most exposed to AI have tripled their lead in workforce productivity growth over the least AI-exposed companies.

40%

Productivity growth is 40% higher at most vs least AI exposed companies.

Companies achieving the biggest productivity gains are boosting wages and headcount

Rather than replacing jobs at scale, leading organisations are using AI to amplify human performance and create value.

52%

The most AI exposed companies see faster headcount growth than the least AI exposed (52% vs 36%) and higher wage growth (24% vs 17%).

Harnessing AI is accelerating skills transformation

Skills required for the most AI exposed jobs are changing twice as fast as in least exposed roles - a 75% increase over last year's gap.

2.5x

The most AI exposed jobs are adding tasks that rely on human-intensive skills like empathy, judgment and creativity 2.5x faster – than the least AI exposed roles.

Redesigned entry level pathways

AI exposed junior roles are 7x more likely (than the least AI exposed junior roles) to demand traditionally senior skills like leadership and strategic thinking.

35%

AI-exposed 'seniorised' entry level roles are thriving with 35% growth since 2019 while other entry level roles decline in number.

A two-track labour market

Jobs professionalised by AI – where AI does the basic work leaving more expert tasks for people (22% of advertised jobs) - are thriving while jobs democratised by AI – where AI takes on the complex work (52% of advertised jobs) - fall behind.

42%

Professionalised jobs are growing twice as fast as Democratised jobs with 42% higher wage growth since 2021.

Implications and next steps

For business leaders

One – Use AI to pursue growth over efficiency alone, using it to unlock new revenue, enter new markets, and create new forms of value, especially by partnering across traditional industry lines.

Two – Consider how AI is changing the human expertise needed for job roles to guide talent investment and skills development.

Three – Invest in agentic AI, the ultimate complement to human expertise. With a team of AI agents at their command, workers can use their uniquely human expertise to deliver value at much greater scale.

Four – Reinvent early career pathways. Redesign onboarding, mentorship, and training programmes to accelerate development of advanced skills like leadership, stakeholder management, and strategic decision-making.

Five – Invest in human-intensive skills alongside AI skills such as empathy, judgment, creativity, and leadership.

For workers

One – Consider moving toward roles made more expert by AI. Our analysis suggests opportunity is migrating from Democratised roles toward Professionalised and low AI exposure roles (with exceptions).

Two – Seek out pioneering companies and industries that are using AI to create new markets or services, or who are partnering across traditional industry lines to invent the new businesses of the future.

Three - Learn to command AI as a tool and partner. Our work suggests that the following saying is true: you won't lose your job to AI but rather to someone who knows how to use AI.

Four – Build human-intensive skills. Hone the skills whose value is rising in an AI era such as creativity, people skills, leadership, judgment, and the ability to navigate complexity and ambiguity.

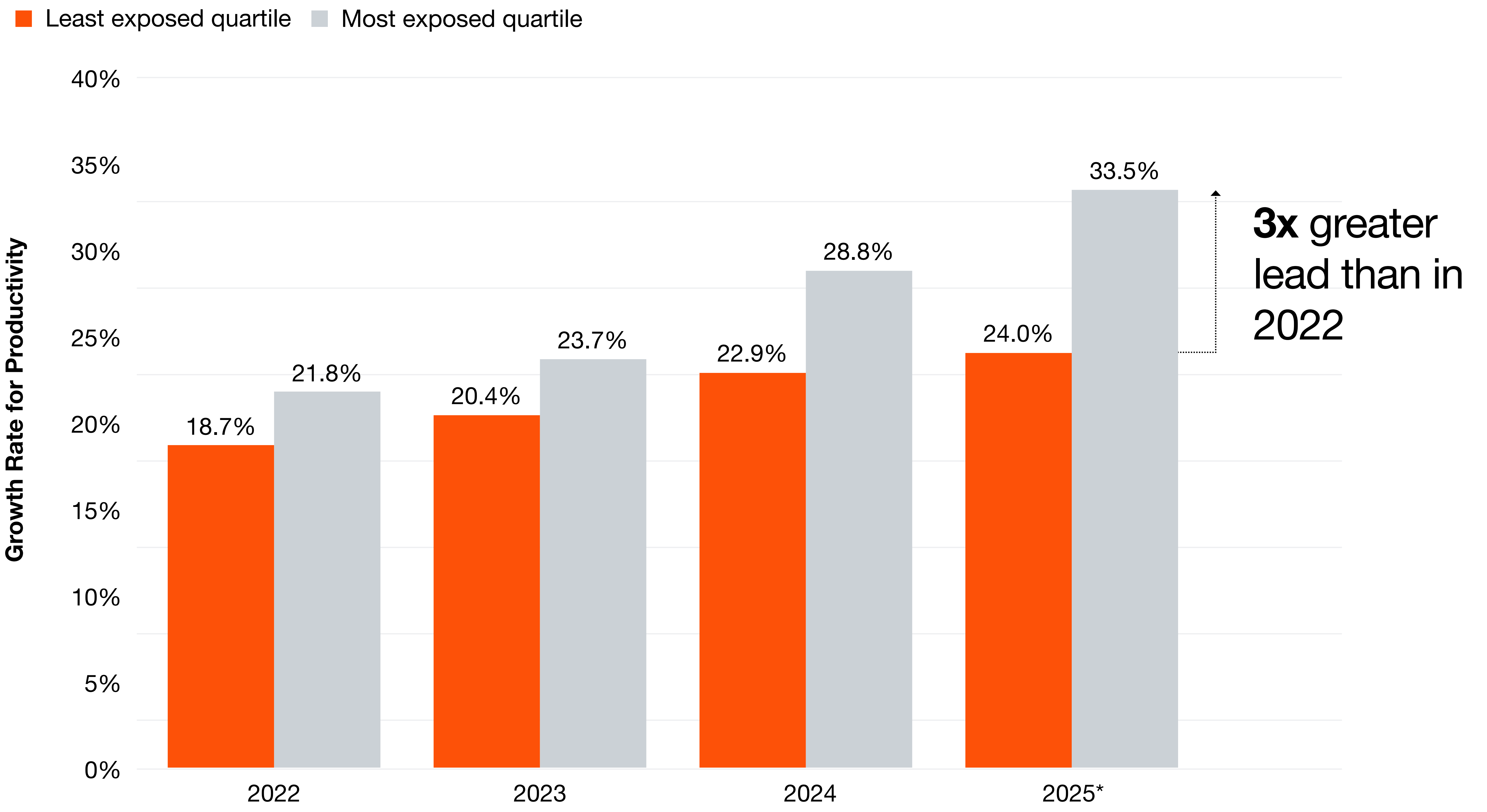
Five – If you are early in your career, develop senior skills fast. Many junior workers may be spared years of drudgery on basic, repetitive tasks – but need to quickly step up to demonstrate skills like leadership and strategic thinking.

1

AI is strongly linked to significant productivity gains for companies

Since 2022 when AI adoption soared, the most AI-exposed companies have seen faster productivity growth

Average firm growth rate in productivity by AI exposure quartile (measured using a 2018 baseline)

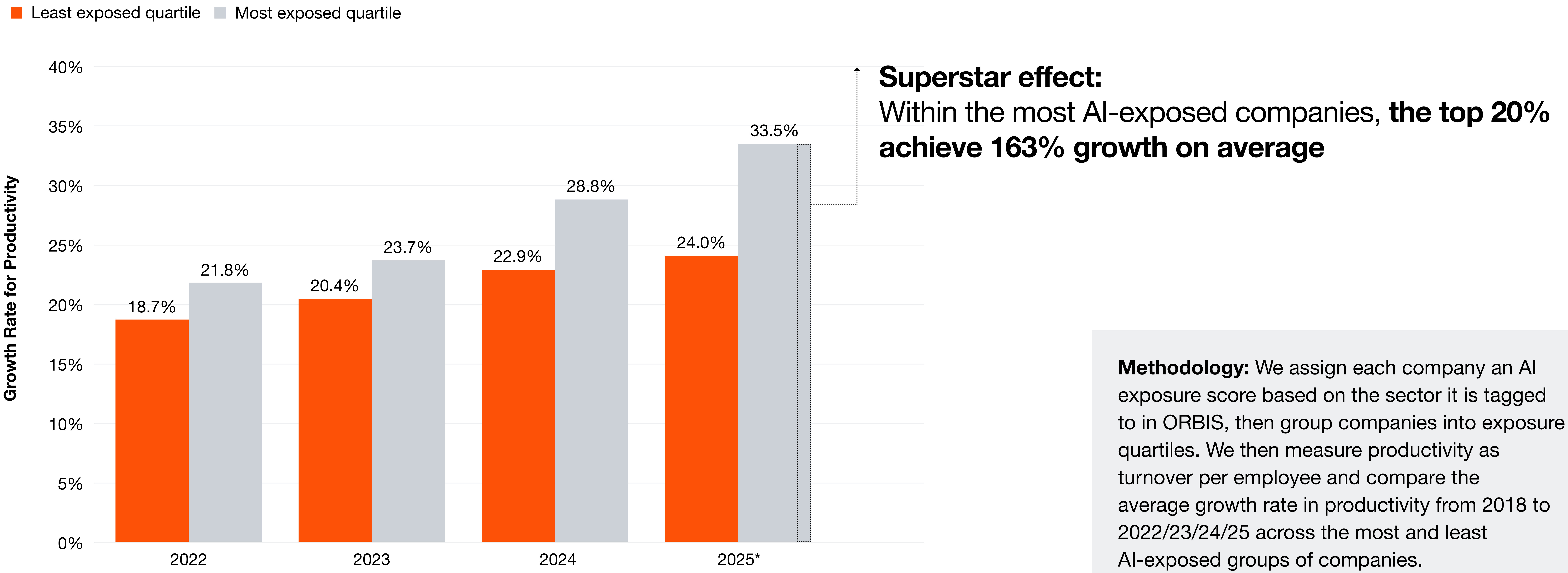


Source: PwC analysis, ORBIS data
Notes: *Productivity is measured by turnover per employee 2018-2024/25. 2025 is data used for companies where available, we substitute missing coverage with 2024 data. Please see appendix for full list of sectors that sit in the least and most exposure quartiles. Company AI exposure is determined by the company sector (for example, is the company in high exposure architecture and insurance, or low exposure mining or waste treatment).

Methodology: We assign each company an AI exposure score based on the sector it is tagged to in ORBIS, then group companies into exposure quartiles. We then measure productivity as turnover per employee and compare the average growth rate in productivity from 2018 to 2022/23/24/25 across the most and least AI-exposed groups of companies.

There is a pronounced 'superstar' effect. The top 20% of most-exposed companies achieve 5x higher topline productivity growth than the most exposed companies as a whole.

Average firm growth rate in productivity by AI exposure quartile (measured using a 2018 baseline)

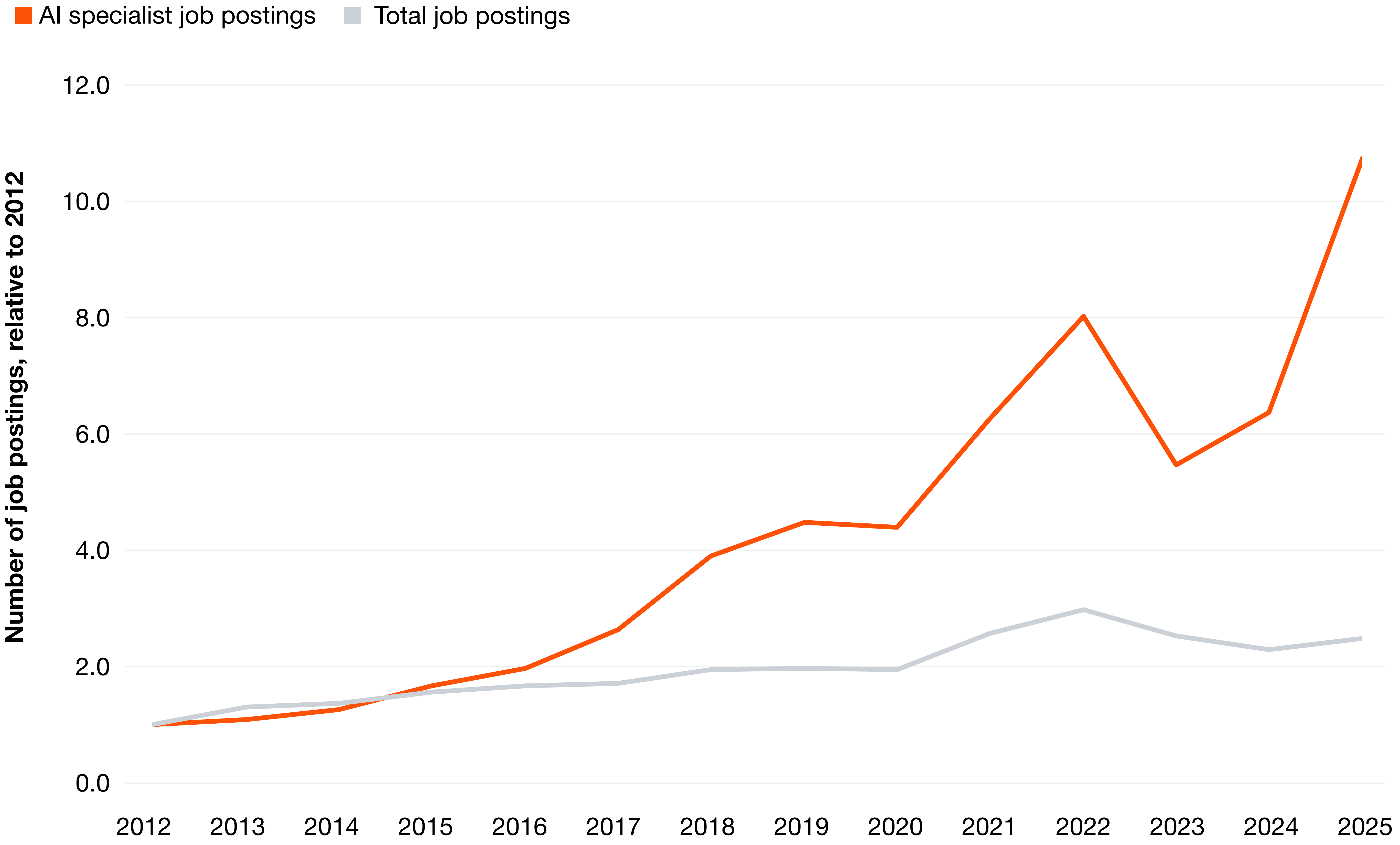


Source: PwC analysis, ORBIS data
Notes: * Productivity is measured by turnover per employee 2018-2024/25. 2025 is data used for companies where available, we substitute missing coverage with 2024 data.

Methodology: We assign each company an AI exposure score based on the sector it is tagged to in ORBIS, then group companies into exposure quartiles. We then measure productivity as turnover per employee and compare the average growth rate in productivity from 2018 to 2022/23/24/25 across the most and least AI-exposed groups of companies.

AI specialist job numbers shot upward in the last year, growing eight times faster than jobs as a whole - indicating companies are prioritising AI investment

Relative growth in AI and all job postings, 2012 to 2025, globally



Source: PwC analysis, Lightcast data
Notes: For some countries, data starts from 2018 or 2021 onwards. As such, we only include the countries for which data is available from 2012 in our sample. AI job postings are defined as those requiring at least one AI-related skill.

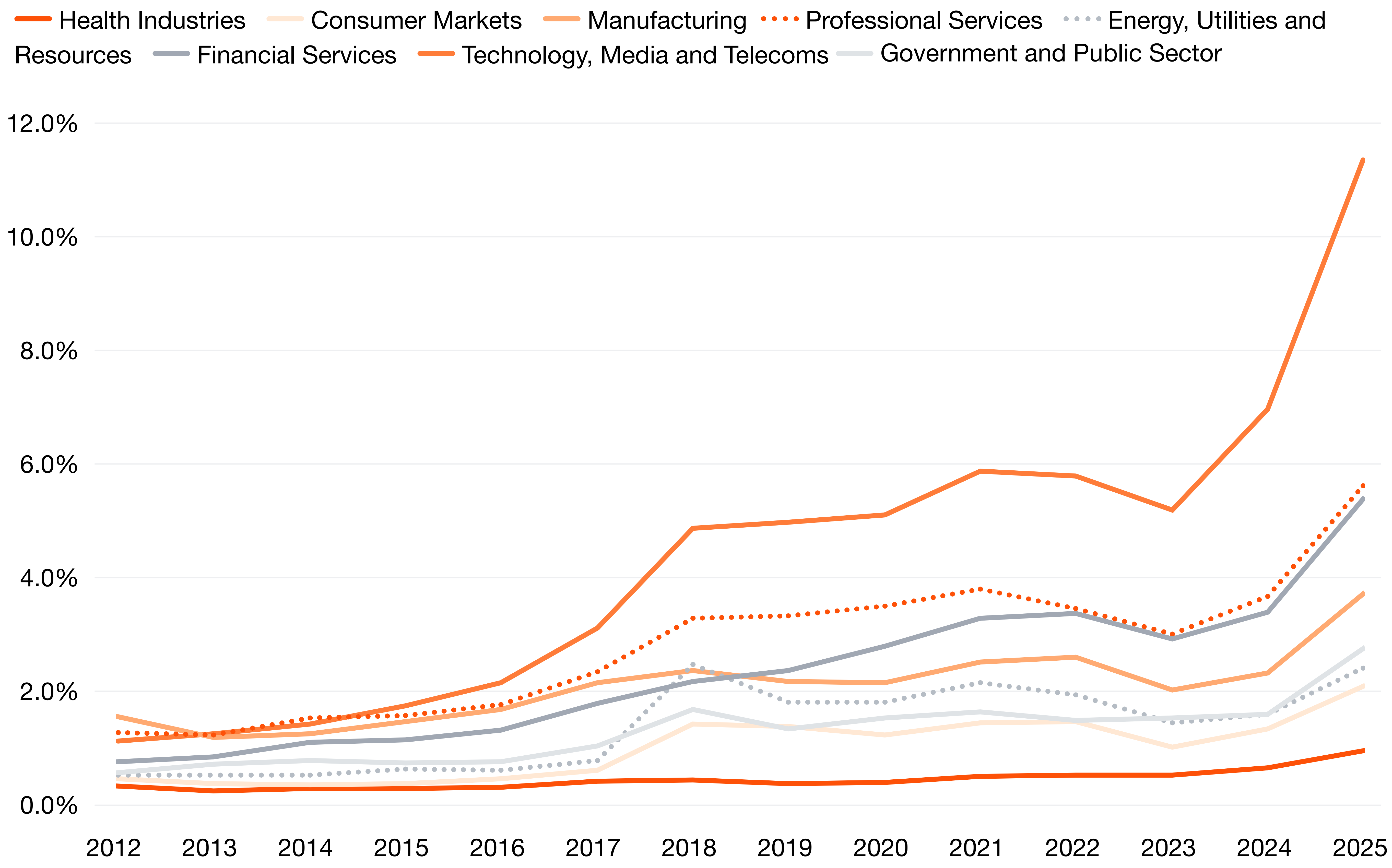
Findings

- 'AI specialist jobs' are jobs that require advanced AI skills such as prompt engineering or machine learning.
- From 2024 to 2025, **AI specialist job postings soared (68.9% rise) while total job growth rose only 8.6%.**
- Growth in AI specialist jobs has outpaced all jobs since 2015. For every one AI specialist job in 2012 there are now 10.7 of these jobs, globally. For other jobs, in contrast, there are now 2.5 jobs.

Methodology: We identify AI specialist job postings as postings requiring at least one AI-related skill from the Lightcast AI skills taxonomy. We then index the number of AI postings and all postings to 2012, allowing us to compare their relative growth through to 2025.

AI specialist hiring is rising in all sectors

Share of AI jobs by sector, globally (%, 2012 to 2025)



Source: PwC analysis, Lightcast data.

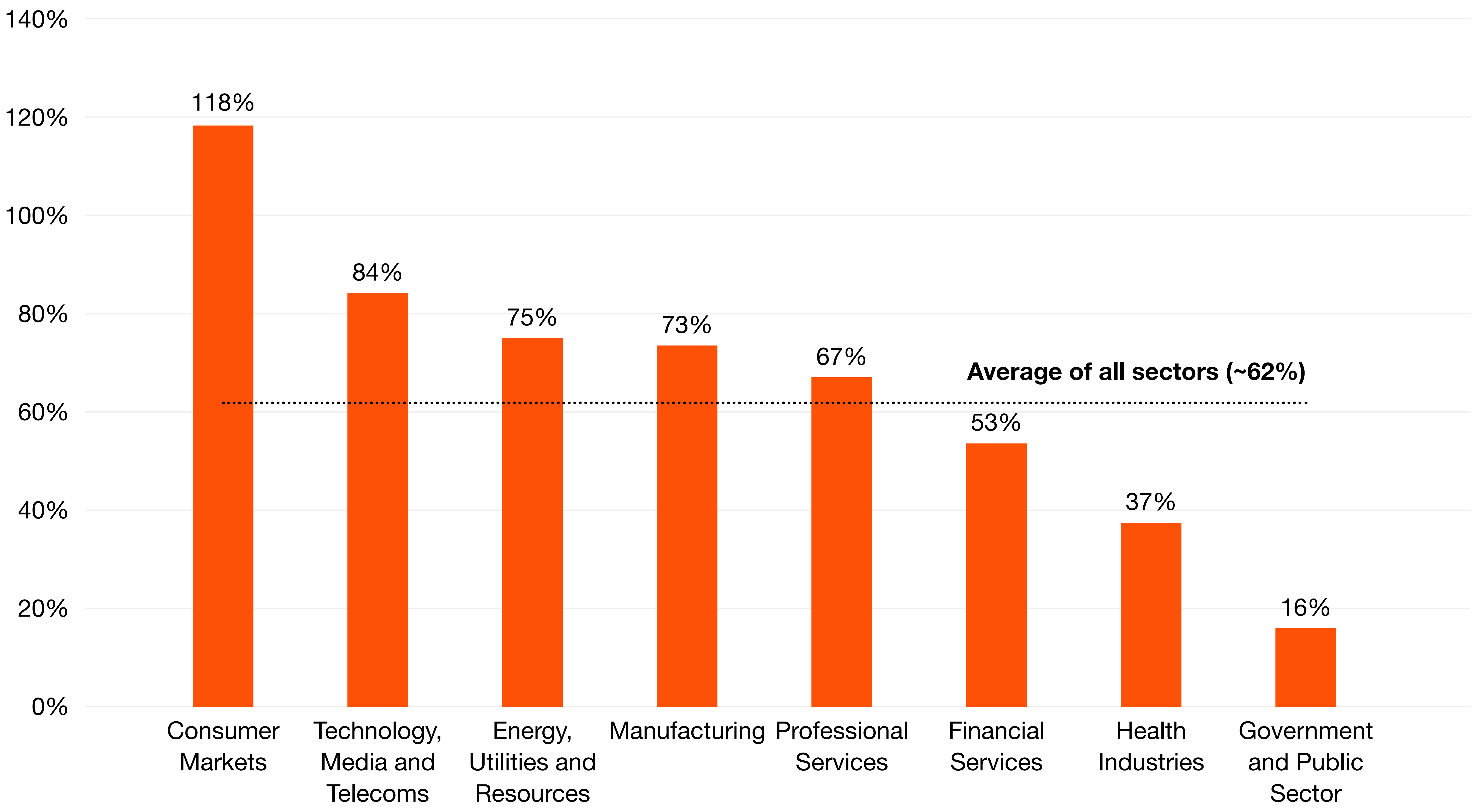
Findings

- Across all key sectors analysed, 2025 saw an increase in the share of AI specialist job postings, indicating broad-based growth in AI hiring.
- Tech, Media and Telecoms (TMT) recorded the highest share at 11.4% in 2025, followed by Professional Services (5.6%) and Financial Services (5.4%).
- While some sectors remain at a lower level of AI specialist hiring, they are still seeing gradual increases. For example, Human Health recorded a 0.9% AI share in 2025, but this continues an upward trend in adoption, increasing from 0.7% in 2024.
- Overall, the data suggests AI specialist hiring growth is occurring across the economy, although at different speeds depending on sector exposure and task composition.

Methodology: For each sector and year, we identify AI-related job postings as those requiring at least one AI-related skill from the Lightcast AI skills taxonomy. We then divide AI postings by total postings in that sector to calculate the share of sector hiring that is AI-related.

Wage premiums for workers with AI skills have risen to 62% (from 57% in last year's Barometer)

Wage premium by sector (%, 2025)



Source: PwC analysis, Lightcast data
Notes: (i) To calculate wage premiums, we split job postings within a sector by AI and non-AI jobs. From here we estimate the wage premium (difference) within the sector for wages in the AI group compared to the non-AI group. This analysis is not a growth rate but rather a snapshot of a given year. Note that only the eight PwC aligned sectors are shown in the visual, however the average of 62% is calculated across all 16 sectors in our AI Jobs Barometer scope.

Findings

- Wage premiums are calculated by comparing the wages offered for similar workers who differ only in whether they possess AI skills such as prompt engineering – for example, by comparing wages for two lawyers, only one of whom has AI skills. (These estimates do not control for other factors that may drive wage differences, such as education, experience, or location.)
- The average AI wage premium across sectors stands at **61.9%,** with most of the key sectors analysed exceeding this benchmark.

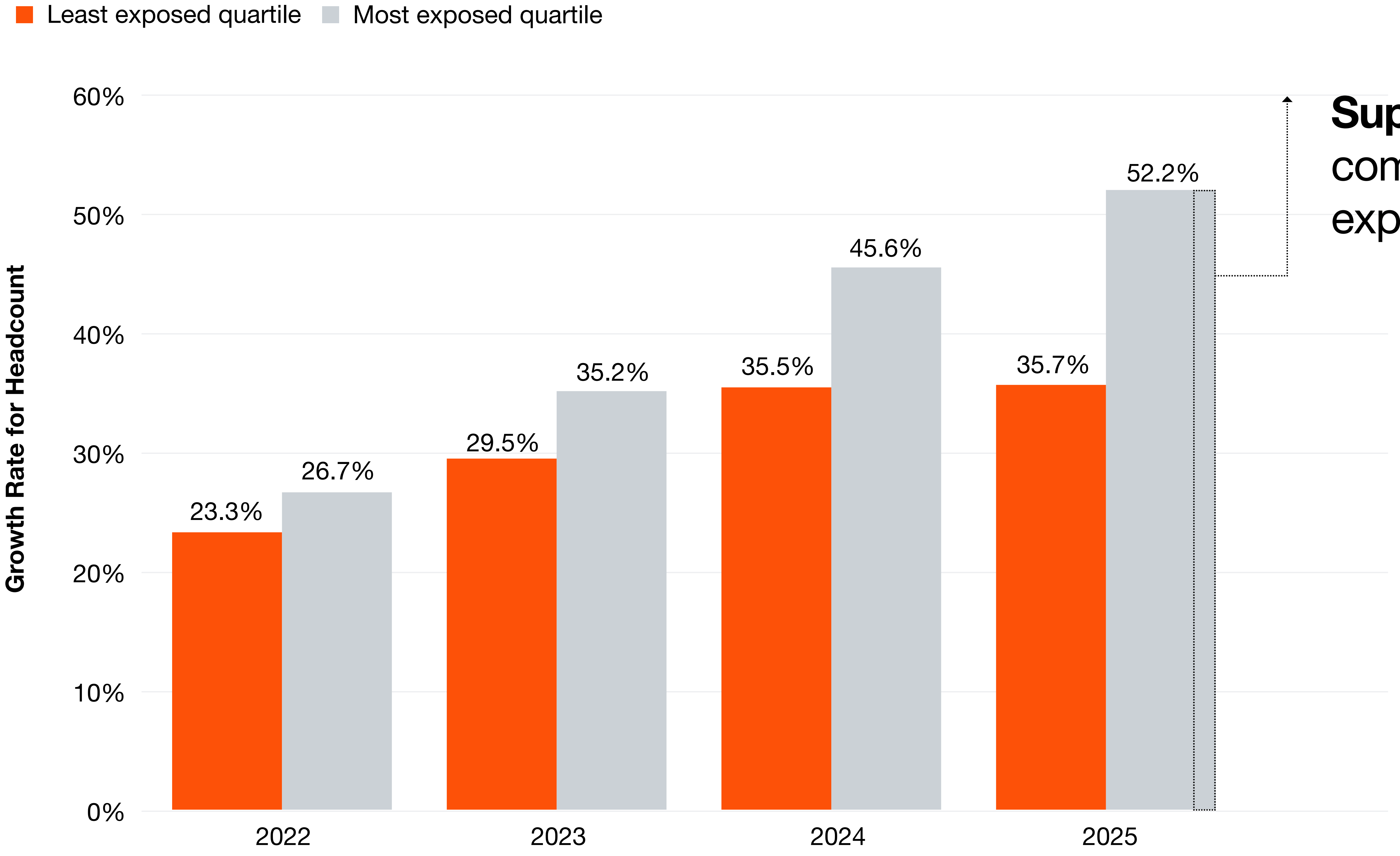
Methodology: Within each sector, we split job postings into AI roles and non-AI roles based on whether they require at least one AI-related skill. We then compare average advertised salaries between the two groups to estimate the AI wage premium as the percentage difference in advertised pay.

2

Companies achieving the biggest productivity gains are boosting wages and headcount

Perhaps surprisingly, headcount growth at the most AI-exposed companies is outpacing that at the least AI-exposed companies

Average firm growth rate in headcount by AI exposure quartile (measured using a 2018 baseline)



Superstar effect: Headcount growth at superstar companies is roughly in line with the rest of the most exposed quartile at 44%.

Source: PwC analysis, ORBIS data

Notes: 2025 is data used for companies where available, we substitute missing coverage with 2024 data. ORBIS company data is not intended to represent economy-wide employment growth. The analysis is based on larger formal firms with available financial and headcount data in both 2018 and 2024/25, including an initial filter for companies with annual turnover of at least $50m USD; firms that exited the market during the period are excluded, creating a survivorship bias. In some countries, financial reporting requirements also vary, meaning firms with consistent reported data may be larger, more formalised or better-performing than the wider business population. The key interpretation is therefore the **relative difference** in headcount growth between more and less AI-exposed companies, rather than the absolute growth rate compared with the broader economy.

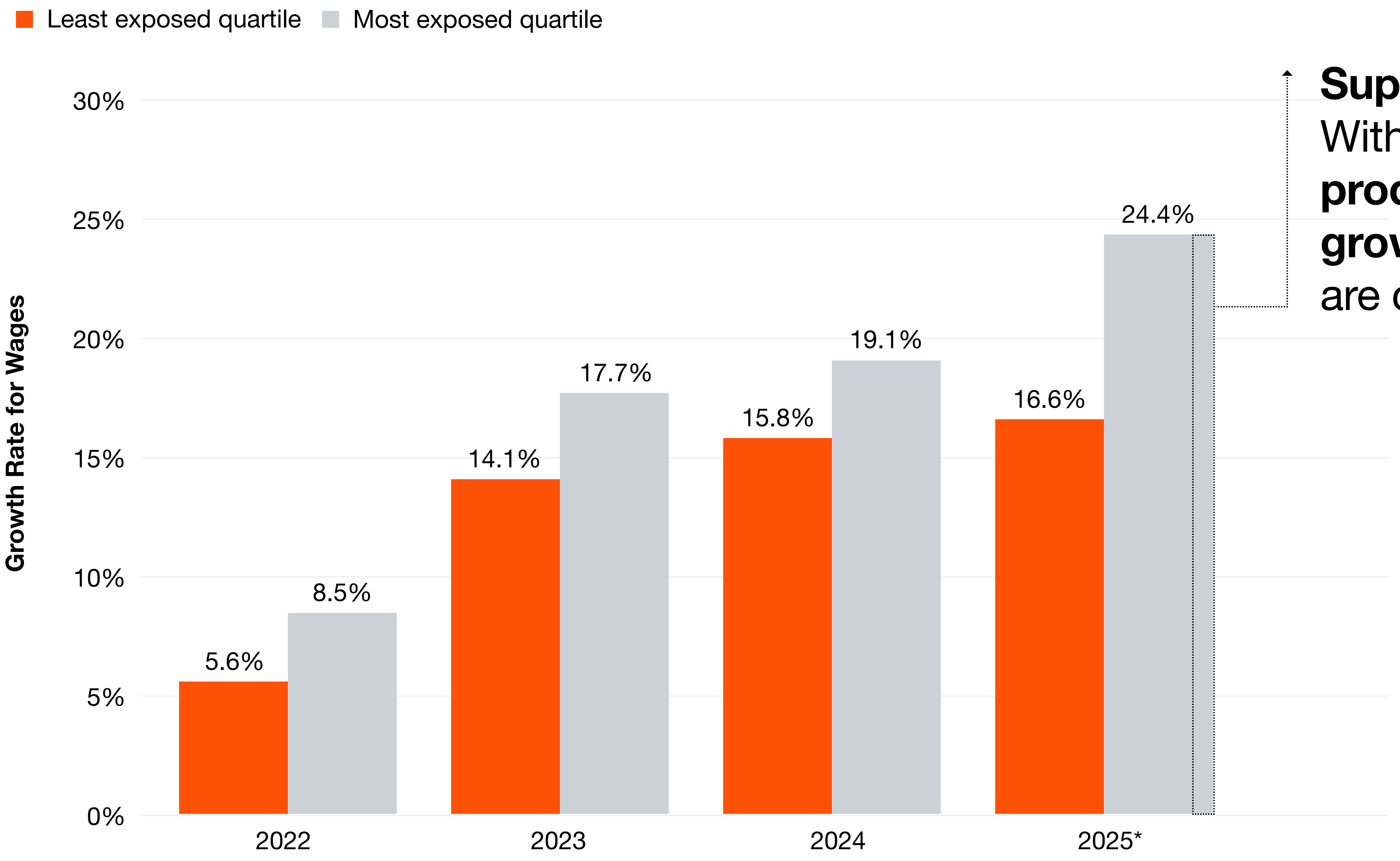
Findings

- This finding aligns with another PwC study, 'Decoding ROI from AI,' which found that 32% of AI performance leaders expect headcount increases of 5% or more, while only 17% of AI underperformers expect headcount increases. **Far from being a job killer, AI may actually be a job expander.**

Methodology: We assign each company an AI exposure scored based on the sector it is tagged to in ORBIS, then group companies into AI exposure quartiles. We then measure headcount growth using ORBIS employee counts and compare average growth rates from 2018 to 2022/23/24/25 across the most and least AI-exposed company groupings.

Wage growth at the most AI-exposed companies has accelerated as productivity rises, suggesting gains are shared with workers

Average firm growth rate in wages by AI exposure quartile (measured using a 2018 baseline)



Superstar effect:
Within the most exposed companies, the **top 20% by productivity growth have even higher average wage growth of 68%** - suggesting AI-driven productivity gains are contributing to higher pay.

Methodology: We assign each company an AI exposure score based on the sector it is tagged to in ORBIS, then group companies into AI exposure quartiles. We then measure wage growth as the change in staff costs per employee, calculated as total staffing costs divided by headcount, from 2018 to 2022/23/24/25.

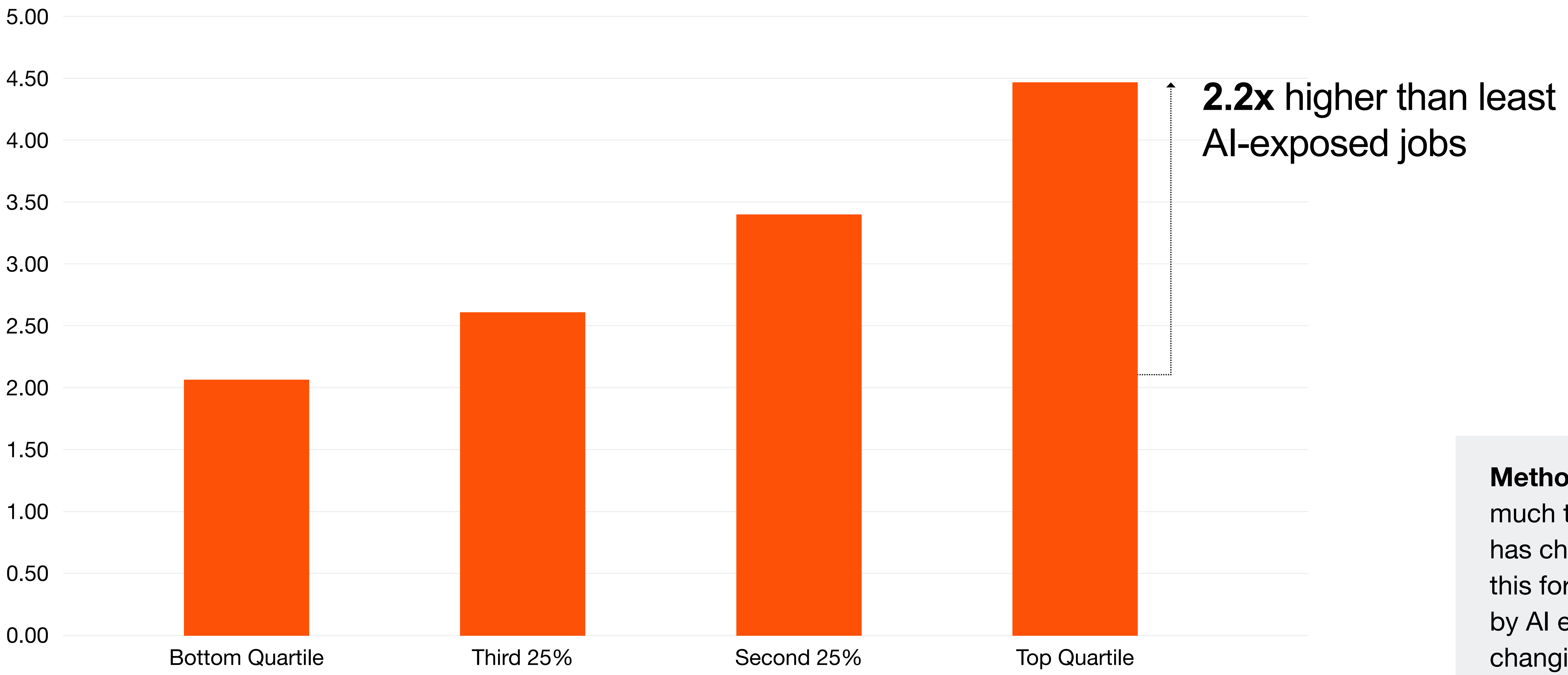
Source: PwC analysis, ORBIS data
Notes: Wages are measured by total staffing cost per employee 2018-2024/25. 2025 is data used for companies where available, we substitute missing coverage with 2024 data.

3

Harnessing AI is accelerating skills transformation

Skills needed for the most AI-exposed jobs are changing more than twice as fast as for the least AI-exposed jobs

Net skill change by AI exposure for all jobs, 2019-2025, globally, by exposure quartile

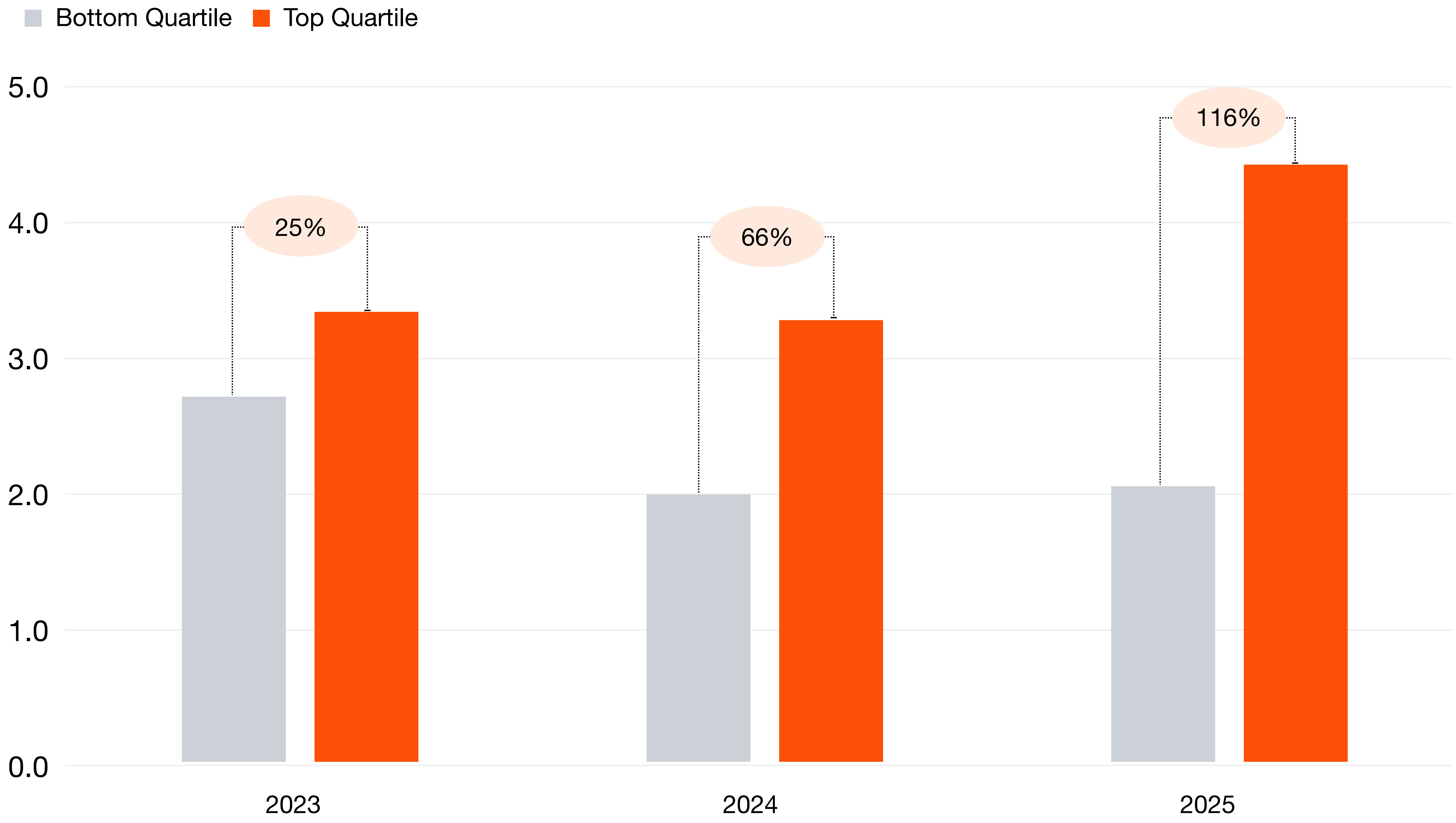


Source: PwC analysis, PwC AI Occupational Exposure Index, Lightcast data
Notes: Net skill change is calculated as the aggregation of the percentage point difference between 2019 and 2025 of the share of a skill making up an occupation.

Methodology: Net Skill Change measures how much the mix of skills required for an occupation has changed between 2019 and 2025. We calculate this for each occupation, then group occupations by AI exposure to compare how quickly skills are changing on average in the most versus least AI-exposed jobs.

The gap is widening over time, with highly AI-exposed occupations seeing faster and faster skills transformation

Net skill change by AI exposure for all jobs from 2019 to 2023, 2024 and 2025, globally, for top and bottom quartile of AI exposure



Source: PwC analysis, PwC AI Occupational Exposure Index, Lightcast data
Notes: Net skill change is calculated as the aggregation of the percentage point difference between 2019 and 2025 of the share of a skill making up an occupation.

Findings

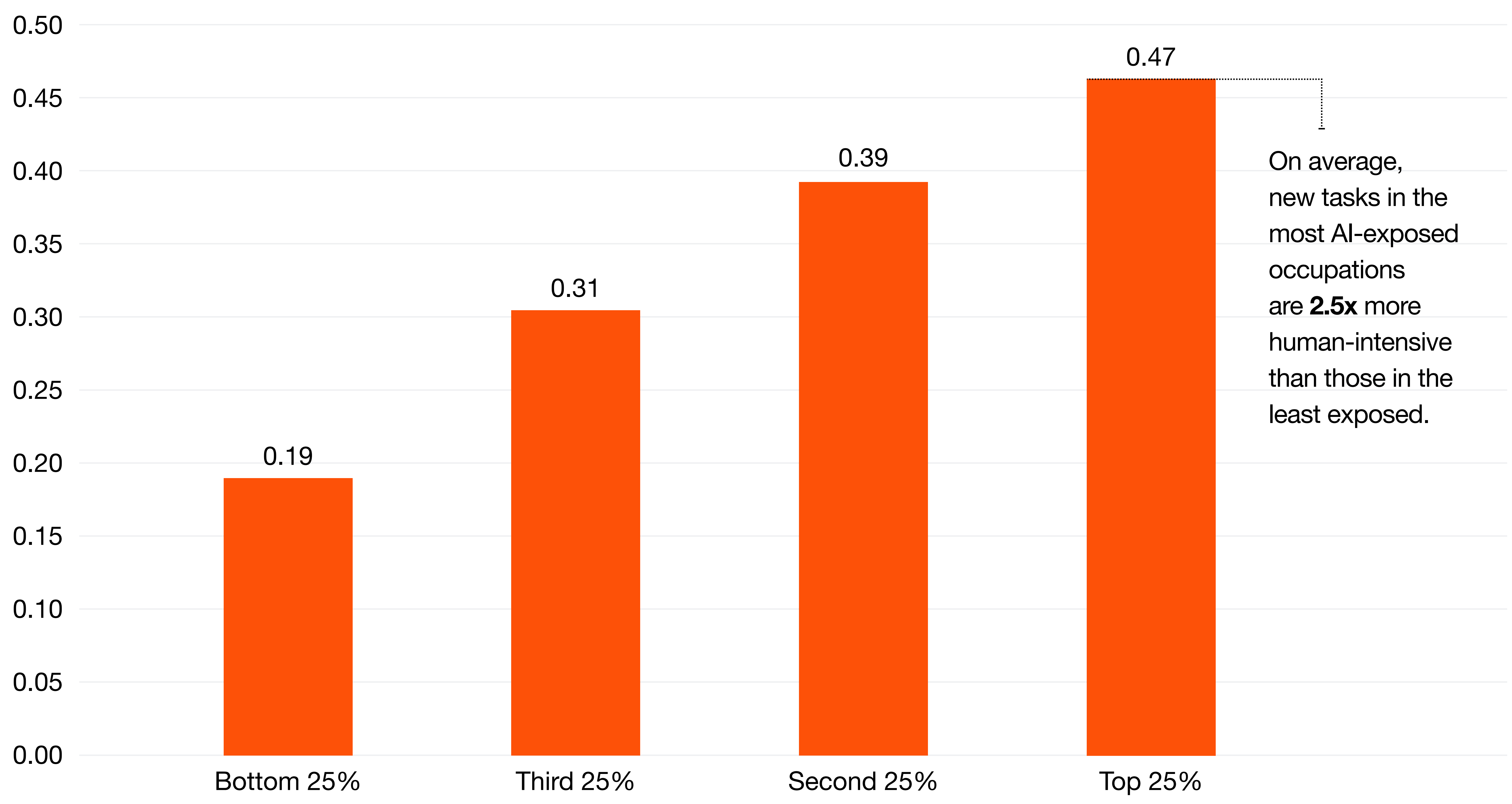
- In 2025, the most AI-exposed occupations evolved at more than twice the rate of the least exposed roles – **a 75% increase over last year's gap.**

Methodology: We use the same Net Skill Change method as the previous slide, but calculate it separately for 2019-2023, 2019-2024 and 2019-2025. We then compare the average Net Skill Change of the top and bottom AI exposure quartiles to show whether the skills-change gap is widening over time.

New tasks added to AI-exposed roles since 2022 are 2.5x more likely to rely on ‘human-intensive’ capabilities such as empathy, creativity, and face to face presence

Average EPOCH score per occupation (new tasks only), by AI exposure quartile, 2022-2025

Top Quartile Average / Bottom Quartile Average: 2.5x



Source: PwC analysis, PwC AI Occupational Exposure Index, Loaiza and Rigobon (2025)
Notes: We draw upon the EPOCH framework, developed by Loaiza and Rigobon (2025) to assess the human intensity of newly emerging tasks. EPOCH scores measure the extent to which tasks rely on human capabilities (Empathy, Presence, Opinion, Creativity, and Hope). We calculate the average EPOCH score of the new tasks in each SOC-2018 occupation, and report averages by AI exposure quartile.

Findings

- We draw on the EPOCH framework, developed by Loaiza and Rigobon (2025). EPOCH is a task-level metric that captures the extent to which tasks rely on five human capabilities: **E**mpathy, **P**resence, **O**pinion, **C**reativity, and **H**ope.
- These human capabilities are typically harder to automate with AI and are more likely to complement the technology. EPOCH scores range from 0 to 1, with higher values indicating greater reliance on human capabilities.

Methodology: We draw from Loaiza and Rigobon’s EPOCH framework to score how much each new task added to O*NET between 2022 and 2025 relies on human-intensive capabilities. We then average these new-task EPOCH scores by occupation, and group occupations by AI exposure quartile to compare how human-intensive new tasks are in the most versus least AI-exposed roles.

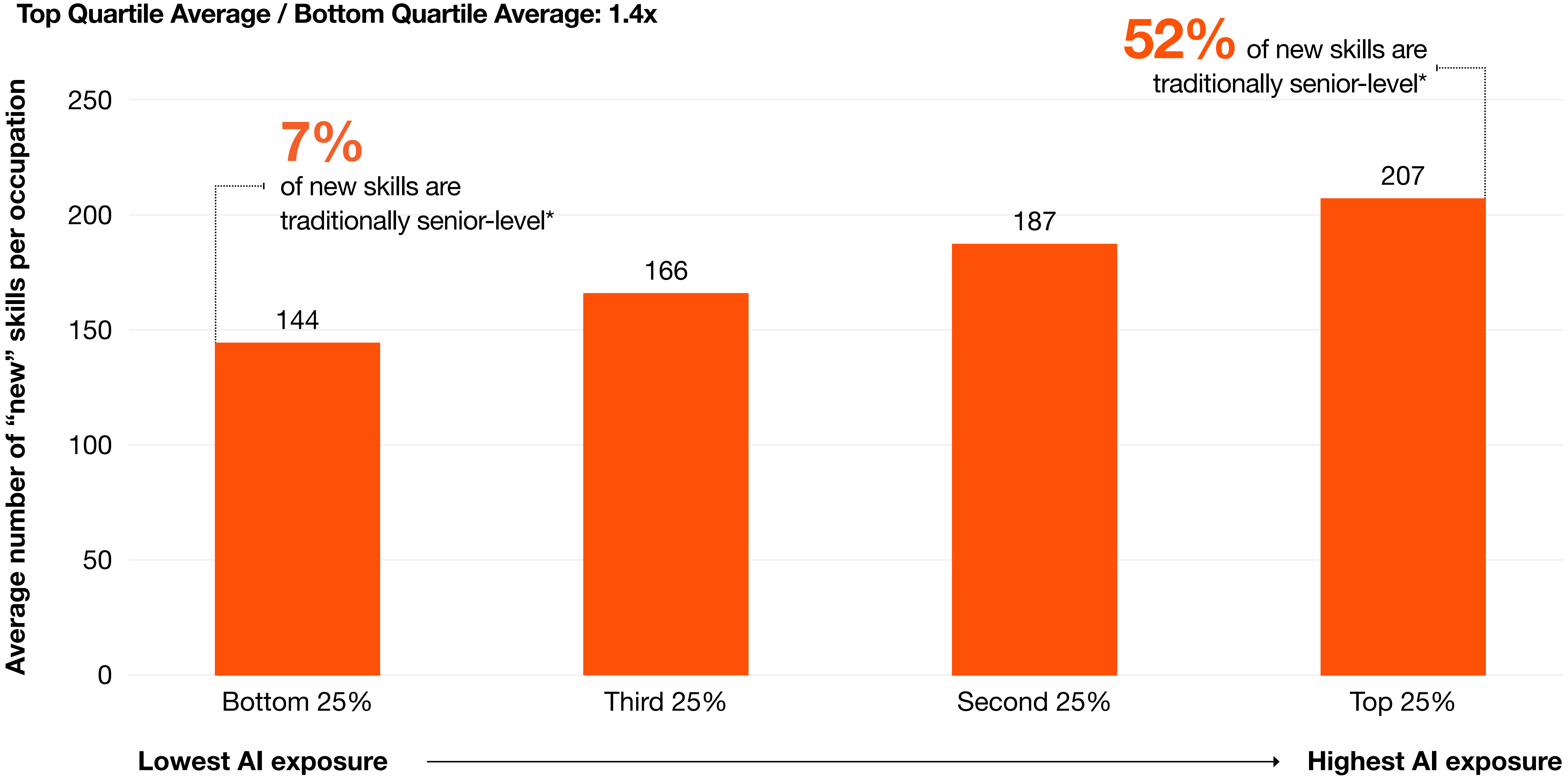
4

Transforming entry level pathways

The most AI-exposed entry level jobs are 7x more likely than the least AI-exposed entry level jobs to now demand traditionally senior skills

Average number of "new" skills per occupation, by AI exposure quartile, 2025 relative to 2019, entry-level job postings, US

Top Quartile Average / Bottom Quartile Average: 1.4x



Source: PwC analysis, PwC AI Occupational Exposure Index, Lightcast data
Notes: (1) Among occupations with a valid PwC AI Occupation Exposure score; (2) A skill is classified as "new" if it has greater than 10 mentions in 2025 but five or fewer mentions in that same occupation in 2019; (3) A skill is defined as traditionally senior if, within the same AI exposure quartile, it had >50 mentions in experienced (non-entry-level) job postings in 2019 and ≤5 mentions in entry-level postings in 2019; (4) *The 52% and 7% are calculated based on unique new skills, rather than total skill occurrences. In the bar charts, skills are counted each time they appear within an occupation (capturing how widely they are used), whereas for the historical comparison each skill is counted only once. As a result, the percentages are not directly comparable to the average new skill values. (5) Because non-entry postings are more numerous than entry-level postings, some skills may be more likely to appear in the non-entry sample. This is unlikely to materially affect the result, as each unique skill is counted once in the historical comparison rather than weighted by total mentions.

Examples of traditionally senior skills now more likely to be required in entry level AI-exposed roles:

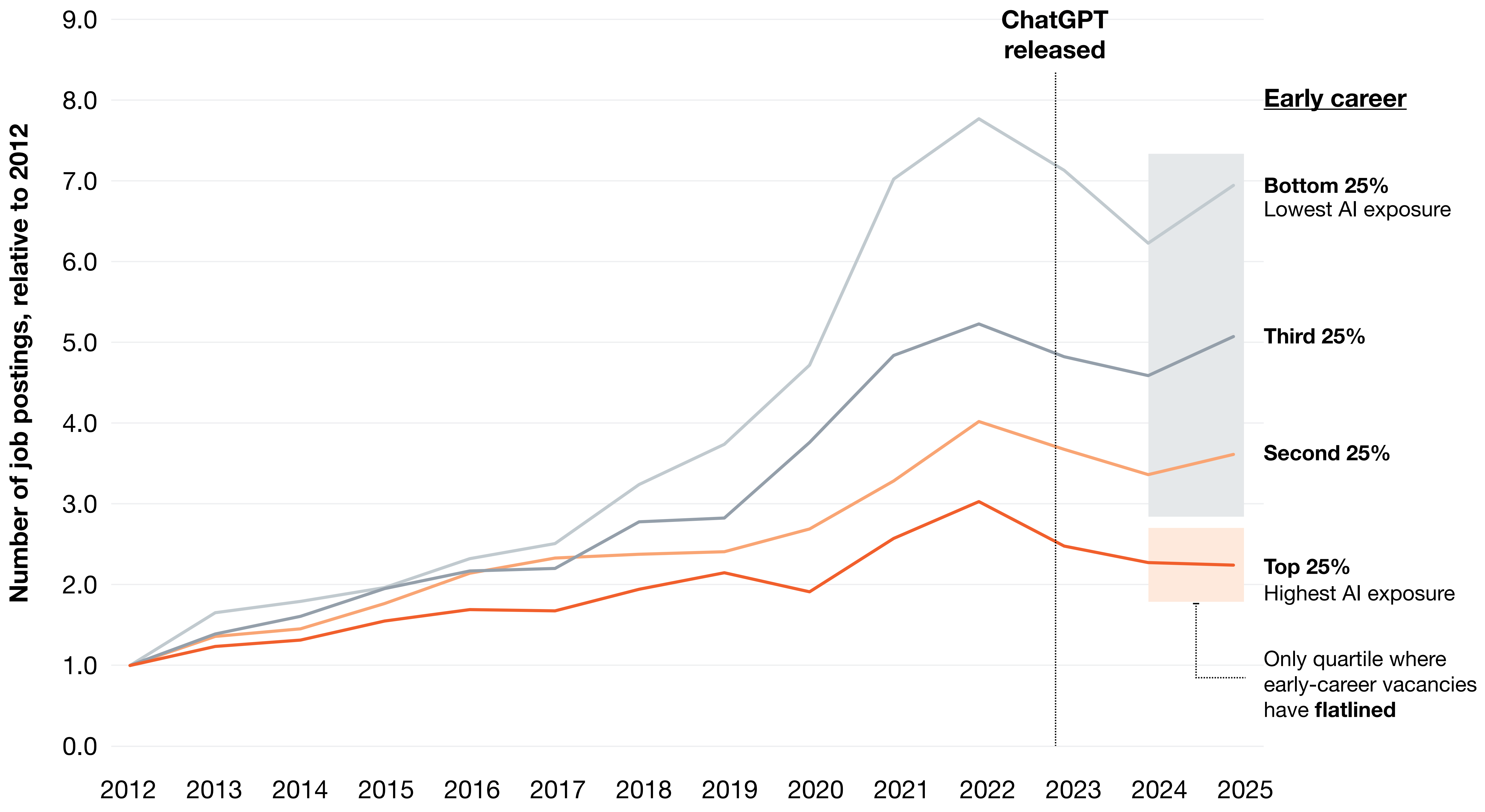
- Strategic decision making
- Motivational leadership
- Team building
- People management
- Stakeholder management
- Process management
- Mentorship
- Resourcefulness
- Data-driven decision making

These skills require EQ, judgment, and leadership.

Methodology: We identify early-career postings as roles requiring 0-2 years' experience, then count 'new' skills for each occupation where the skill appears more than 10 times in 2025 but five or fewer times in 2019. To assess seniorisation, we flag new skills as traditionally senior if they were common in experienced postings in 2019 but rare in early-career postings, then compare the share of these skills across AI exposure quartiles.

Across advanced economies, job postings are growing more slowly for entry level workers more exposed to AI

Number of early-career job postings relative to 2012, by AI exposure quartile, global

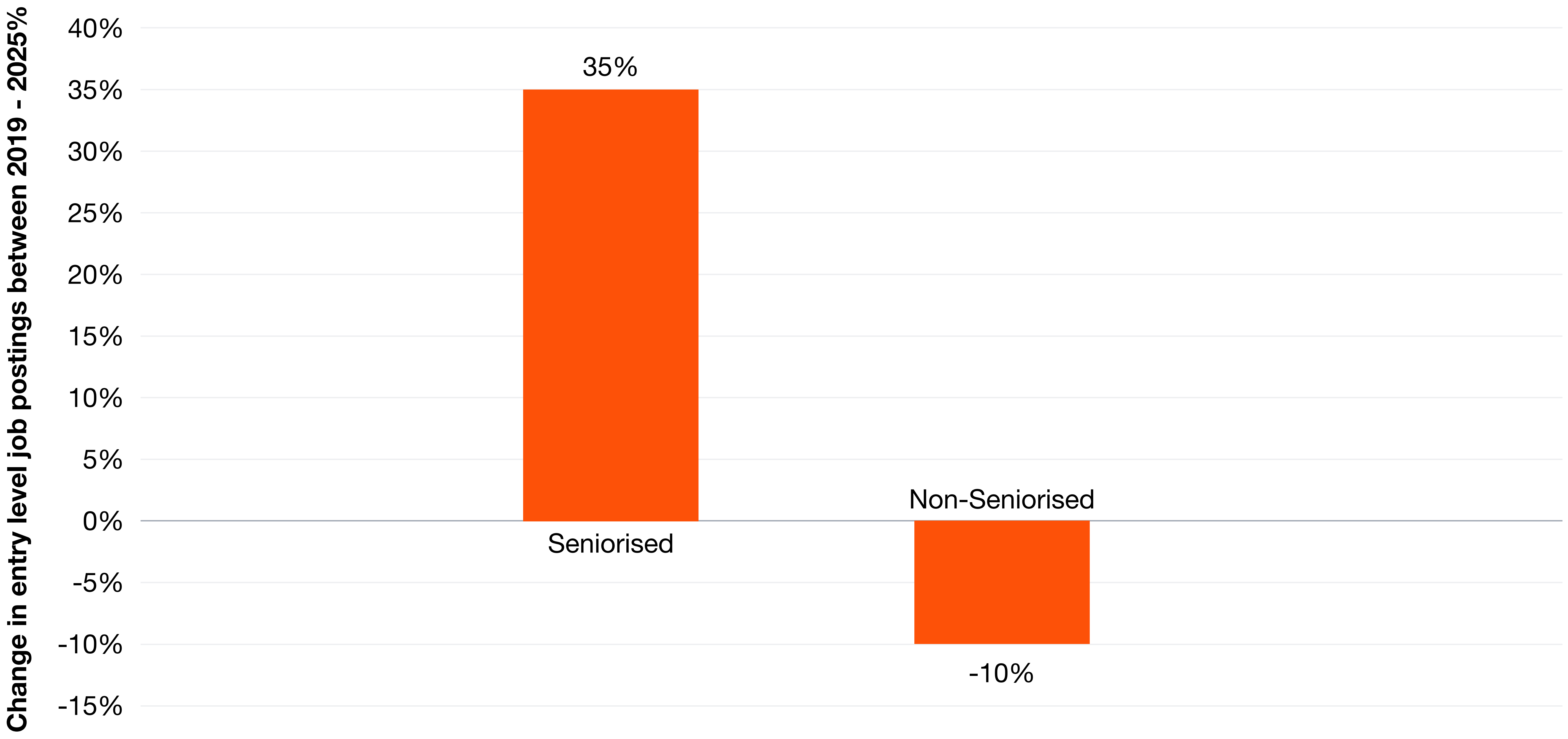


Source: PwC analysis, Lightcast data
Notes: The "Years of Experience" variable from Lightcast is used as a proxy for early-career jobs. A posting is defined as an early-career job if its years of experience listed is between 0-2 years. Due to data availability, we only include the following countries in our analysis: Canada, Singapore, UK and US (1) Careful interpretation of this chart is necessary – this is not to say AI is causing these impacts. Other shocks / structural characteristics of occupations in the Top 25% may also contribute to the observed trend. (2) Results are mainly driven by US data which accounts for c.73% of total job postings in the sample of countries with data available from 2012.

Methodology: We define early-career postings as roles requiring 0-2 years of experience, then assign each posting to an AI exposure quartile based on its occupations' PwC AI Occupational Exposure score. We then count early-career postings in each quartile each year and index the totals to 2012 to compare relative growth over time.

But look deeper, and AI-exposed entry level roles have very different job growth outcomes depending on whether they are being upskilled to demand more traditionally senior abilities

Change in entry-level job postings between 2019 and 2025, seniorised vs non-seniorised roles, top AI exposure quartile, US



Source: PwC analysis, Lightcast data
Notes: (1) An entry-level job posting is classified as “seniorised” if it contains ≥10 mentions of a skill that is both new and traditionally senior. A skill is defined as new for a given occupation if it has >10 mentions in entry-level postings in 2025 but ≤5 mentions in entry-level postings for the same occupation in 2019. A skill is defined as traditionally senior if, within the same AI exposure quartile, it had >50 mentions in experienced (non-entry-level) job postings in 2019 and ≤5 mentions in entry-level postings in 2019.

Methodology: We focus on early-career postings in the top AI exposure quartile and classify them as ‘seniorised’ if they contain newly emerging skills that were traditionally concentrated in experienced roles in 2019. We then compare posting growth from 2019 to 2025 for seniorised versus non-seniorised early-career roles.

5

A two-track jobs market

AI is having two different impacts on jobs depending on whether it is automating more or less expert[1] tasks

52% of jobs are being

DEMOCRATISED

(shifted toward less expert tasks)

Example: Inventory Clerk

More expert tasks like manage inventory

AI automated

Less expert tasks like move stock

Remain

22% of jobs are being

PROFESSIONALISED

(shifted toward less expert tasks)

Example: Recruiter

More expert tasks like negotiate contracts

Remain

Less expert tasks like screen CVs

AI automated

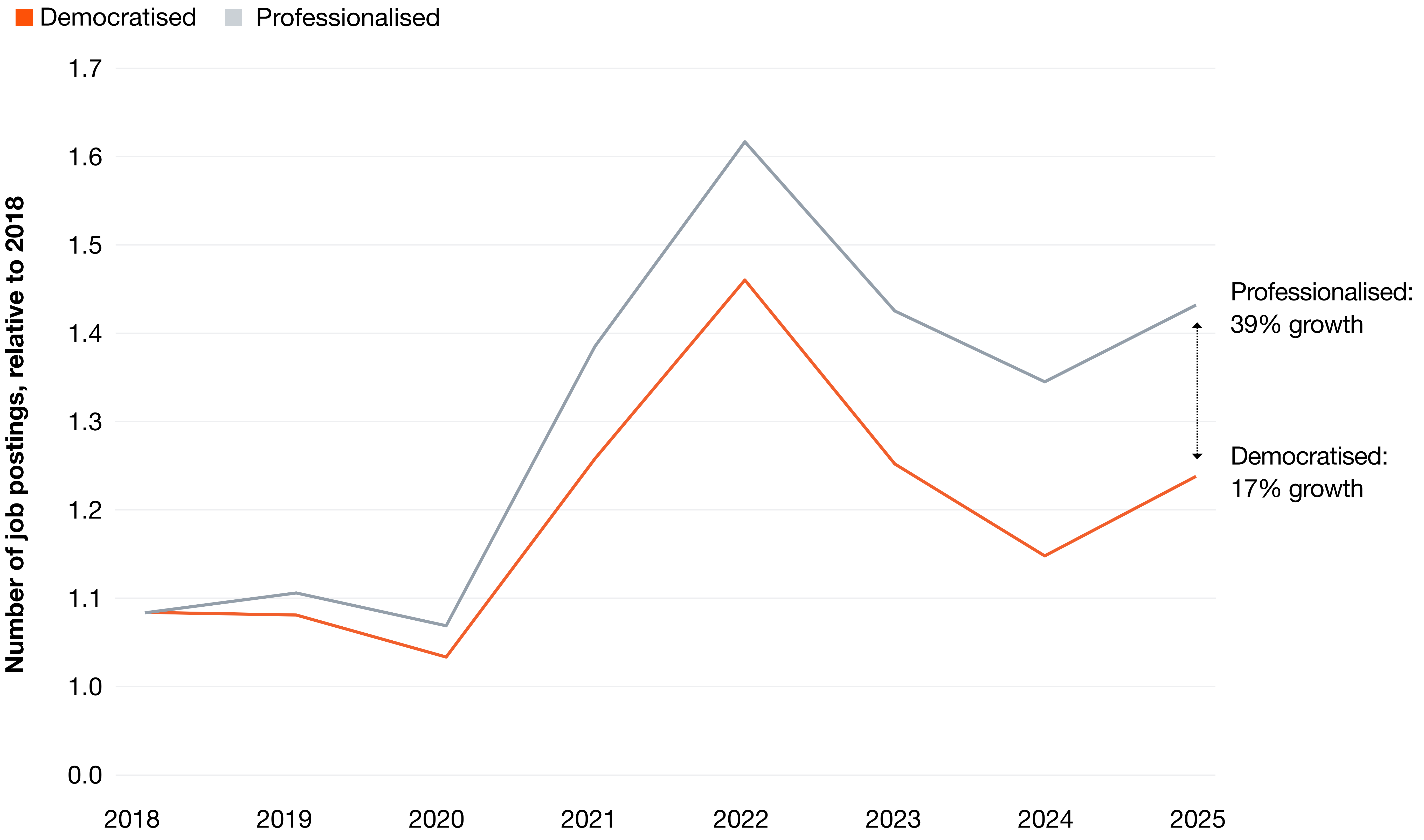
10 examples of Democratised occupations	
Interior designers	Software developers
Contact centre information clerks	IT service managers
Medical secretaries	Construction supervisors
Systems administrators	Web technicians
Accounting clerks	Process control technicians

10 examples of Professionalised occupations	
Client information workers	Valuers and loss assessors
Research and development managers	Dispensing opticians
Religious professionals	Musicians, singers and composers
Environmental engineers	Personnel and careers professionals
Executive secretaries	Air traffic controllers

[1]expert = requiring specialised knowledge or capability

Professionalised jobs are growing twice as quickly as Democratised jobs

Number of job postings relative to 2018, 2018-2025, democratised and professionalised jobs, global

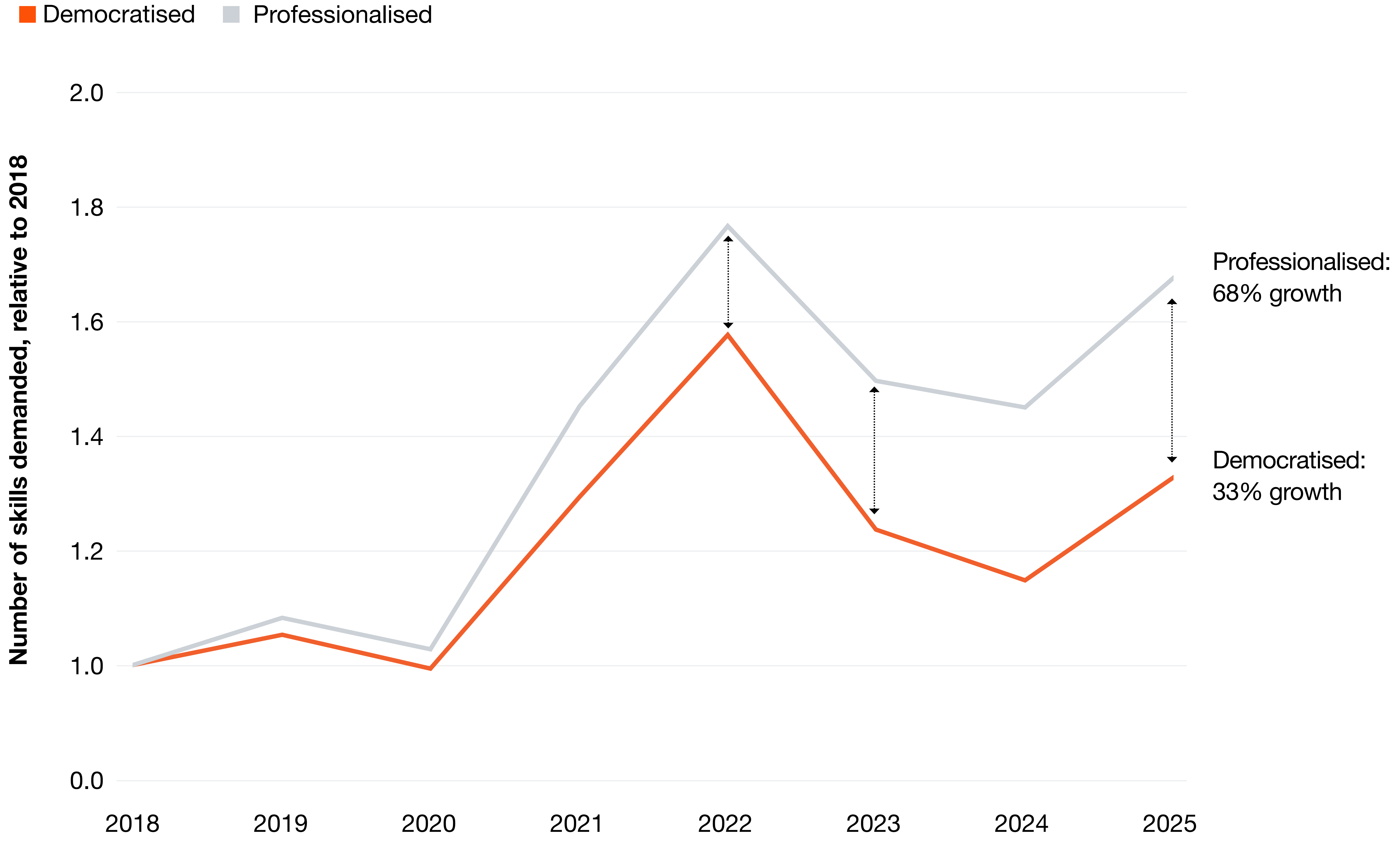


Source: PwC analysis, Lightcast data, Teeselink and Carey (2026)
Notes: Due to data robustness, we only include the six countries for which Lightcast data is available from 2012 onwards.

Methodology: We draw upon data from Teeselink and Carey (2026) to classify occupations as Professionalised or Democratised, based on whether AI shifts the role toward more or less expert tasks. We then map these classifications to Lightcast job postings, count postings in each group each year, and index the totals to 2018 to compare relative growth over time.

Professionalised roles are demanding additional skills at twice the rate of Democratised roles, and the gap has widened since 2022

Number of skills demanded relative to 2018, democratised vs professionalised occupations, global

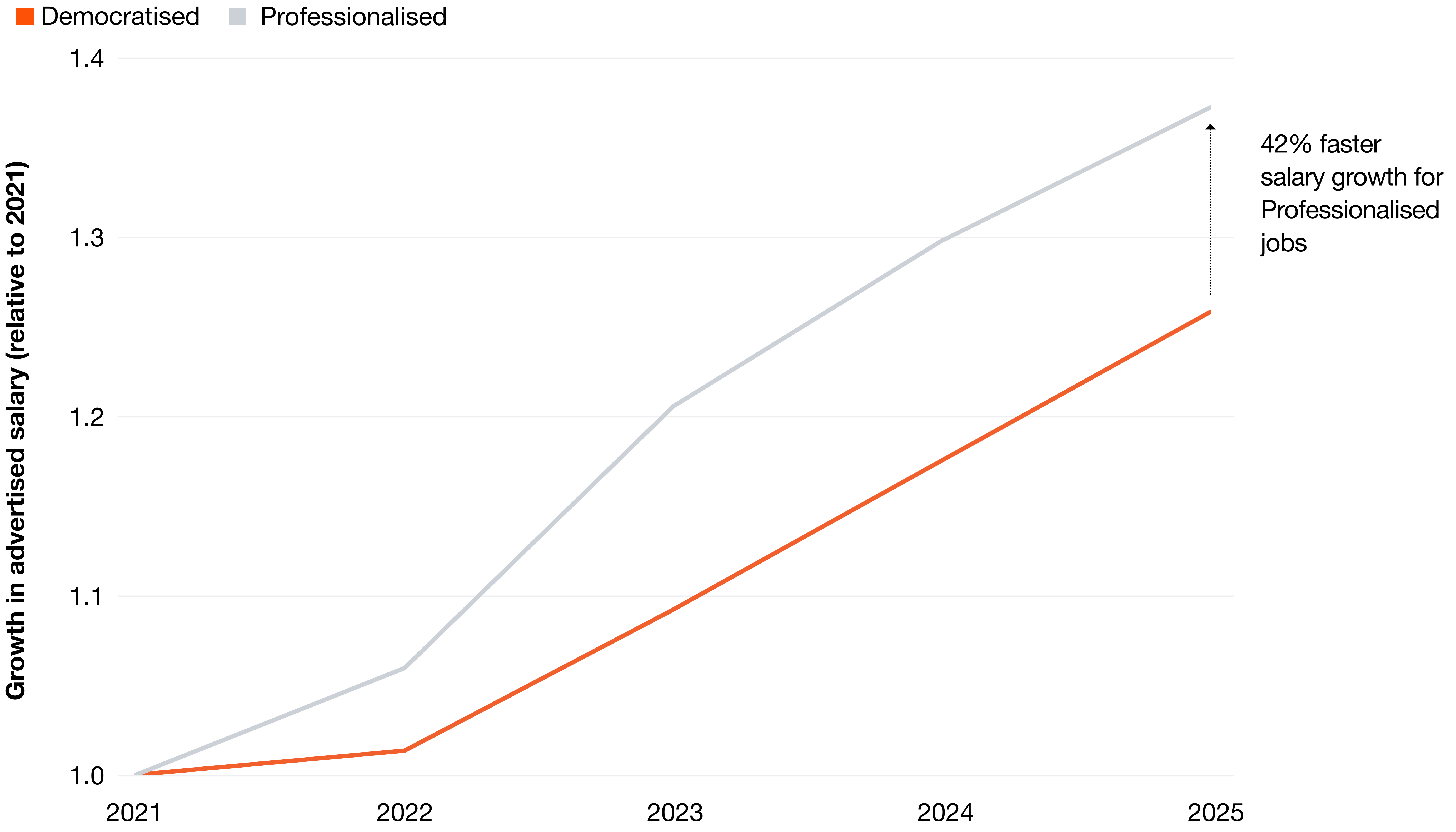


Source: PwC analysis, Lightcast data, Teeselink and Carey (2026)
Notes: Due to data robustness, we only include the six countries for which Lightcast data is available from 2012 onwards.

Methodology: We draw upon Teeselink and Carey's (2026) expertise data to classify each occupation as Professionalised or Democratised, then apply this classification to Lightcast postings. We count the skills mentioned in postings within each group each year and index the totals to 2018 to compare how quickly skills demand is growing.

Professionalised roles have seen 42% faster growth in average salaries relative to Democratised roles, with a growing gap from 2022

Growth in average advertised salary, democratised and professionalised jobs, relative to 2021, global



Teeselink's expertise data was provided to us at SOC-2018 level. SOC classification in Lightcast jobs data is not available outside of the US. Thus, in order to produce global figures and metrics for our expertise analysis using Lightcast data, we map Teeselink's expertise scores from SOC-2018 to ISCO-08 for this purpose only. Professionalised salaries have grown 37% since 2021 and Democratised by 26% - a 42% gap.

Source: PwC analysis, Lightcast data, Teeselink and Carey (2026)
Notes: Due to data robustness, we only include the six countries for which Lightcast data is available from 2012 onwards.

Methodology: We draw upon Teeselink and Carey's (2026) expertise data to classify postings as Professionalised or Democratised based on their occupation. We consider only postings with advertised salary data available. For each group and year, we calculate average advertised salary as total advertised salary divided by postings with salary information, then index the results to 2021 to compare growth over time.

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:

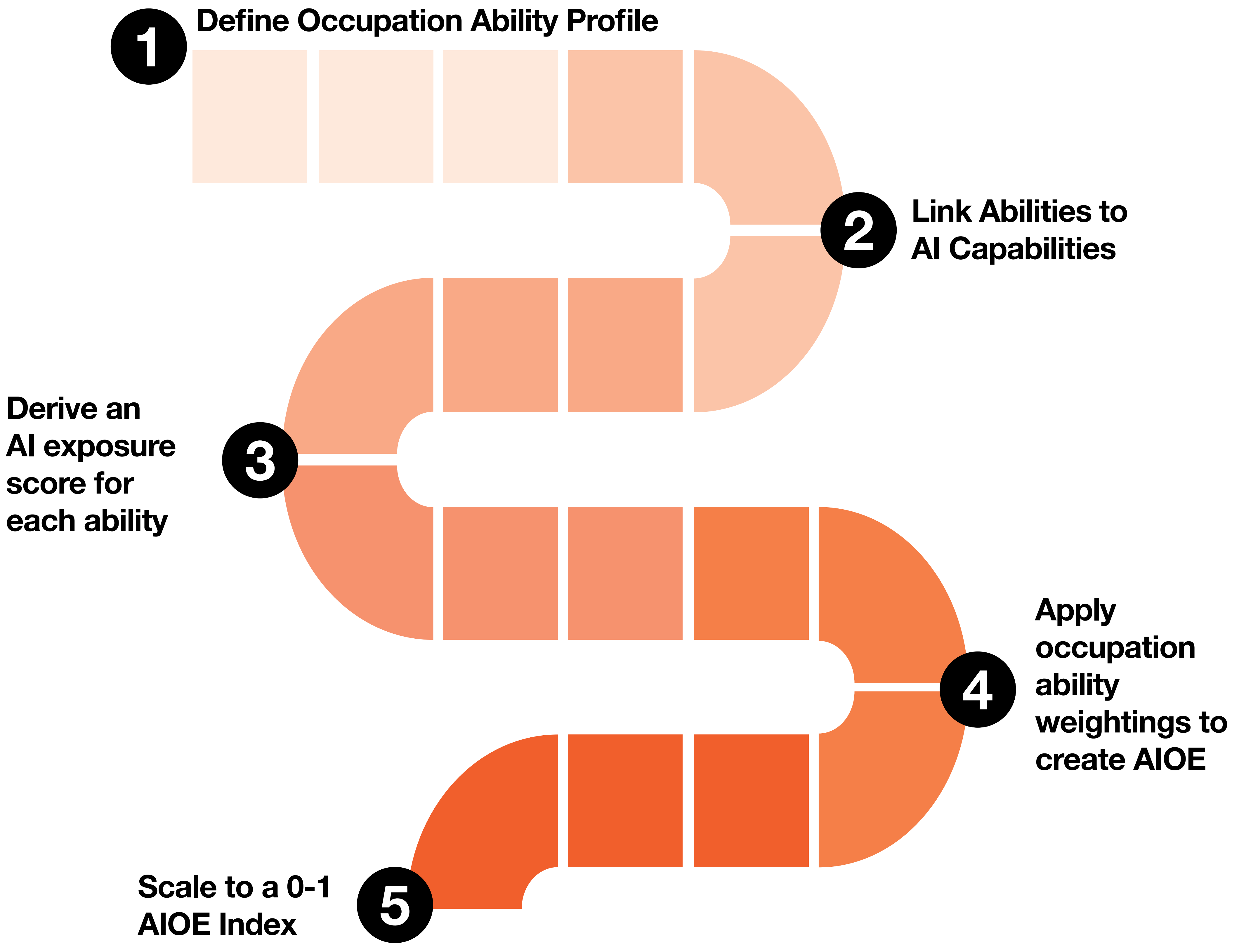
We update the O*NET Abilities dataset to capture new occupations and revised ability weights

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

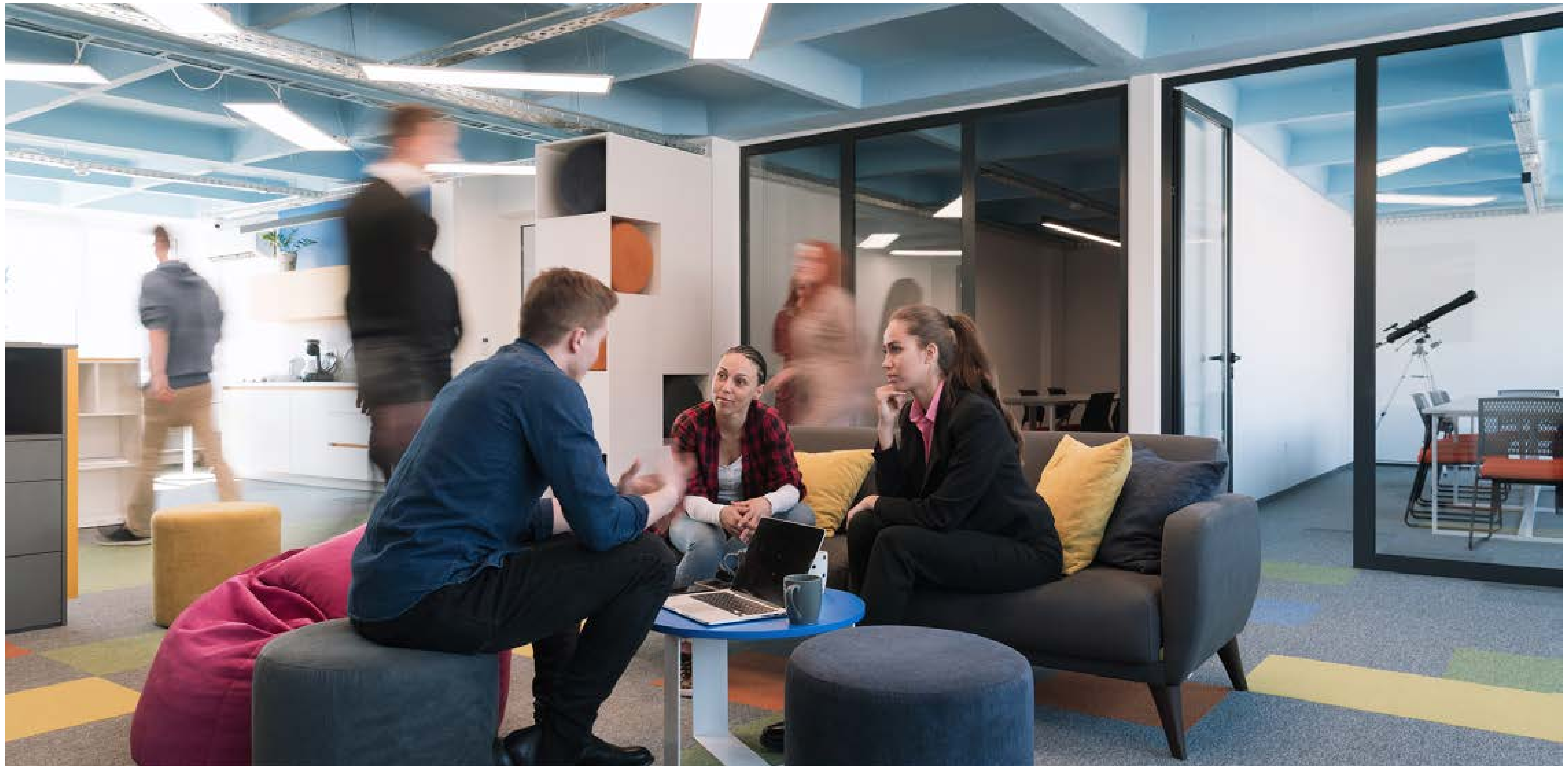
The PwC AI Industry Exposure Index builds on Felten et al. (2021)'s AI Industry Exposure framework, which measures how exposed industries are to AI based on the relationship between occupational requirements and AI capabilities. Felten's original industry index was produced at NAICS level using US occupation-by-industry 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

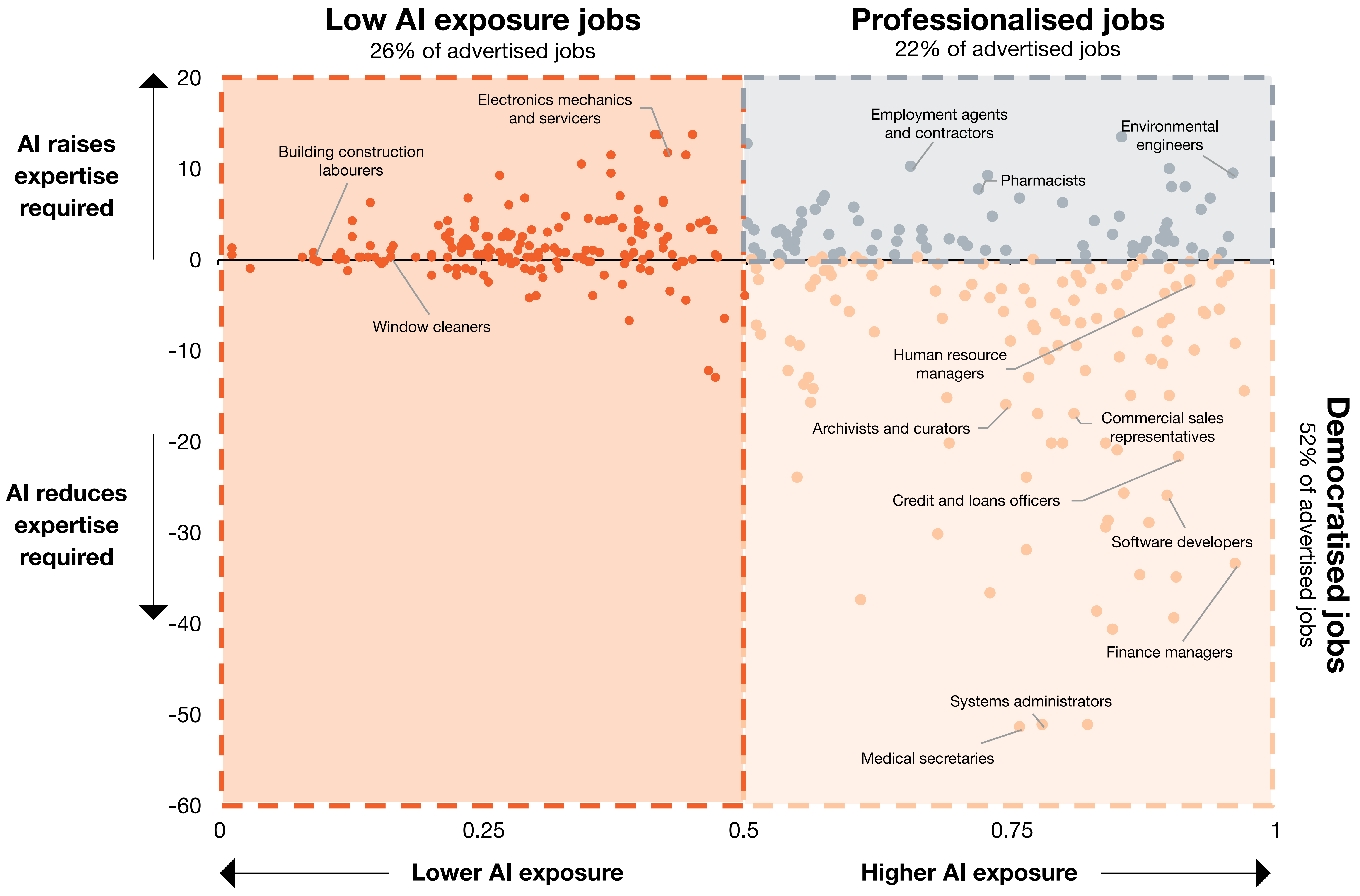
Countries included in the analysis and the number of postings analysed for each country

#	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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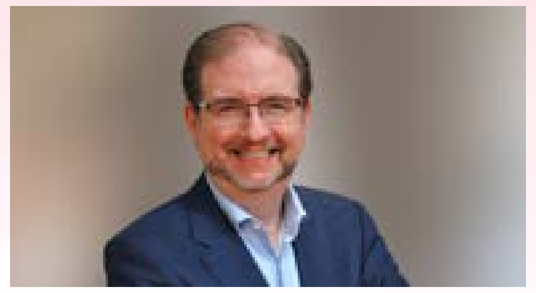


Joe Atkinson
Global Chief AI Officer for the PwC Network of Firms, PwC US

Peter Brown
Global Workforce Leader, PwC UK

Thought Leadership Creation

Sarah Brown
Thought Leadership Lead, Global Communications and Change, PwC UK

UK Economics Research Team

Simon Oates
UK Economics Leader, PwC UK

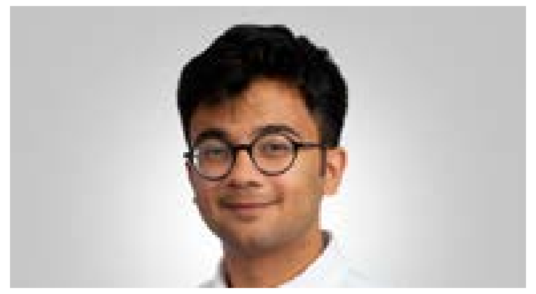
Nabil Taleb
Economist, Manager, PwC UK

Harry Ingham
Economist, Senior Associate, PwC UK

Zara Sendut
Economist, Associate, PwC UK

Mehdi Sahneh
Economist, Senior Manager, PwC UK

William Feng
Economist, Senior Associate, PwC UK



Mustafa Rupawala
Economist, Senior Associate, PwC UK

Senior Advisors

Annie Veillet

Partner, Cloud, Data and AI, PwC Canada

Zlatina Loudjeva

Partner, Engagement Leader for AI Skills Hub, UKRI's AI Skills Hub, PwC UK

Anthony Bruce

Partner, Global Health Industry Leader, PwC UK

Khaled Bin Braik

UAE Country Senior Partner, PwC UAE

Anumeha Singh

Partner, Organisation and Talent Transformation, PwC India

Marlene de Koning

Director, Transformation Consulting, AI and Adoption, PwC Netherlands

Bas Van De Pas

Partner, Transformation Consulting, AI and Adoption, PwC Netherlands

Parul Munshi

Partner with PwC South East Asia Consulting, APAC Workforce Leader, PwC Singapore

Bivek Sharma

Chief Technology and AI Officer, PwC Middle East

Prasun Shah

Partner, Global CTO, Workforce Consulting, Chief AI Officer, PwC UK

Brenda Vethanayaga

Partner, Risk Services, AI Trust, PwC Canada

Rob Dicks

Partner, Commercial AI Lead, PwC US

Chris Greenwood

Lead Partner, Corporate Function Transformation, PwC Australia

Rusbeh Hashemian

Global Technology Leader, EMEA CIO & CTO, PwC Germany

Dan Priest

Chief AI Officer, PwC US

Scott Likens

Global Chief AI Engineer, PwC US

Dr Dayalan Govender

Partner, People and Organization Transformation Leader, PwC South Africa

Shebani Patel

Partner, Workforce Solutions Practice Leader, PwC US

Farbod Nassiri

Partner, National Practice Lead, Digital HR Transformation, PwC Canada

Vikas Agarwal

Global and US Commercial Chief Technology & Innovation Officer, Advisory, PwC US

Felicity Copeland

Director, Trust in AI, PwC UK

Vishy Narayanan

Asia Pacific Digital & AI Leader, PwC Malaysia

Julia Lamm

Partner, Workforce Transformation, PwC US

Justine Brown

Director, Global Workforce, PwC UK

2026 Global AI Jobs Barometer

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