Beyond technology: how labour market competition shapes AI adoption

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Foreword

Artificial intelligence has moved to the centre of the business agenda. Leaders see its potential to reshape work, unlock productivity gains and create new sources of value. Yet when we look inside organisations, adoption often seems patchy and slow. Some employees lean in; others hesitate.

The question behind this research is straightforward: **is AI's technological potential on its own enough to drive adoption, or do people also need a stronger "push" from incentives, particularly labour market forces?**

To explore this, we look at more than 600 occupations through two lenses. We focus on the occupational level and not the firm level because, ultimately, the decision to use AI rests with the individual employee. It is the person doing the work who chooses whether to use the technology into their workflow, making them the central figure in driving adoption.

The first is generative **AI exposure** – how far the tasks in an occupation could be transformed by AI, given today's capabilities. The second is **Labour market competition** – how strong the competitive incentives are for workers in that occupation to change the way they work.

With our econometric analysis, **we find that for most occupations – when AI exposure is not very low nor very high – having high Labour market competition increases AI use.**

By bringing these perspectives together, we can see where AI is likely to be pulled into day-to-day work by market competition, and where organisations will need to be more deliberate in creating incentives, for example through AI literacy programmes. Technology alone doesn't drive change; leaders and workers do, by aligning capabilities, incentives and trust.

The AI productivity puzzle: divergence between micro potential and macro outcomes

Data tells a conflicting story. On the one hand, recent studies indicate that AI can sharply raise productivity in specific roles and tasks. On the other hand, we do not yet see a broad-based acceleration in GDP or economy-wide productivity – a new version of the long-standing "productivity paradox".

Why does the evidence at the micro level fail to scale immediately to macro outcomes? To explore this, we need to consider three angles: micro-level field experiments, macro-level growth modelling, and the structural lags inherent in technological diffusion.

1. The micro evidence: validating technological potential

At the level of individual tasks, the evidence for productivity gains is robust. To give just one example, an analysis of the rollout of a generative-AI assistant in a large customer service operation finds a 14-15% productivity increase in issues resolved per hour.[1] While the evidence in other contexts may not always be as clear-cut, these results confirm that the technological capability to drive productivity exists today.

2. The macro reality: structural constraints on scaling

The challenge lies in translating these micro gains into aggregate growth. Nobel Laureate economist Daron Acemoglu utilises a task-based model to project macro outcomes.[2] His conclusion offers a necessary counterweight to optimism: under realistic assumptions about which tasks are automated and how quickly AI diffuses, the immediate addition to annual productivity and GDP growth may be modest.

Acemoglu argues that unless AI usage shifts from narrow automation to a broader redesign of work, the aggregate impact remains constrained.

This is because simple substitution yields limited efficiency gains. Similarly, economist David Autor's recent work on AI and expertise emphasises that the most inclusive gains will emerge only if AI is used to extend the reach of human expertise – enabling more workers to perform high-value tasks – rather than simply displacing existing ones.[3]

3. The "Productivity J-Curve": the investment lag

This divergence between technology and output is often framed in terms of a "Productivity J-curve". As with previous general-purpose technologies, the initial phase of adoption requires firms to invest heavily in intangible assets: data infrastructure, skills, and process re-engineering.[4]

These investments are costly and often poorly measured in standard accounts. Consequently, measured productivity may appear flat, or even decline, before it accelerates. Technology alone is not enough; the macroeconomic impact depends on broad, effective adoption. This requires organisations to move beyond the technology itself and create the incentives and capabilities for workers to integrate AI into their tasks.

The role of market forces

Our analysis of AI exposure and Labour market competition speaks directly to this adoption challenge. It suggests that while the technical potential is high, the incentive "push" is not automatically present.

The misalignment between capability and market incentives means that AI adoption will be uneven. As the "J-curve" suggests, realising the macroeconomic gains predicted by theory will require not just better algorithms, but deliberate organisational changes driven by competitive pressure and strategic intent.

1 Brynjolfsson, Erik, Danielle Li, and Lindsey Raymond. "Generative AI at work." The Quarterly Journal of Economics 140.2 (2025): 889-942.
2 Acemoglu, Daron. "The simple macroeconomics of AI." Economic Policy 40.121 (2025): 13-58.
3 Autor, David. Applying AI to rebuild middle class jobs. No. w32140. National Bureau of Economic Research, 2024.
4 Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. "The productivity J-curve: How intangibles complement general purpose technologies." American Economic Journal: Macroeconomics 13.1 (2021): 333-372.

Measuring AI potential and labour market competition

Our starting point is the technological side of the story. For AI exposure, we draw on the seminal work of Eloundou et al. (2023),[5] who estimate how generative AI and related technologies affect the task content of occupations in the United States (US). While model capabilities have continued to advance since this baseline was established, recent research confirms that the relative distribution of exposure across occupations remains robust.[6]

Their approach links model capabilities to detailed task descriptions and produces an AI exposure score for each occupation – a forward-looking measure of how susceptible that occupation is to AI-enabled change.

This is a capability-side measure: it tells us where AI can go at the moment, not whether it actually has.

How the AI exposure is constructed and why it is all about tasks

The AI exposure scores indicate how close, in terms of abilities required for specific tasks, different occupations are to what today's AI systems can do. In this context, "exposure" means that access to AI – for example a large language model or an application built on top of it – could meaningfully reduce the time needed for a human to complete a task while keeping quality at least as high.

Crucially, exposure does not directly predict employment or wage loss. Instead, it signals where work could change and which workers are more likely to need to adapt as AI tools improve and diffuse. The scores focus on the technical feasibility of using AI; they do not fully capture other drivers of adoption such as regulation, organisational choices, culture or worker preferences. Being among the "least exposed" occupations also does not mean escaping AI's impact altogether, and the underlying framework does not account for new jobs or tasks that may emerge because of AI.

AI, however, does not act on job titles – it acts on tasks. Therefore, each detailed task in the US O*NET database is assessed for how much it could be affected by AI. Some tasks – such as drafting text, coding, analysing data or summarising documents – are judged to be highly exposed. Others – such as hands-on physical work or face-to-face service – are far less affected by current AI capabilities. These task-level exposure assessments are then aggregated into an occupation-level score, giving more weight to the core tasks that define a job. The occupational AI exposure scores in this report are therefore best read as summaries of how deeply AI reaches into the bundle of tasks that make up each occupation, rather than binary labels of whether a job is "safe" or "at risk".

5 Eloundou, Tyna, et al. "Gpts are gpts: An early look at the labor market impact potential of large language models." arXiv preprint arXiv:2303.10130 10 (2023).
6 Gmyrek, Paweł, et al. Generative AI and jobs: A refined global index of occupational exposure. No. 140. ILO Working Paper, 2025.

To complement this, we construct a novel Labour market competition index that captures how strong the economic incentives are for workers in each occupation to change the way they work. Whereas AI exposure is about what AI can do, Labour market competition is about the workers' need to adapt.

The index combines several labour-market indicators. Some variables increase exposure to market forces, others reduce it. A higher percentage of self-employed workers, for instance, tends to go hand in hand with higher exposure: individuals bear more commercial risk directly, and their livelihoods depend more heavily on remaining competitive.[7] Higher separation rates – more people leaving jobs over a given period – also point to a more fluid labour market in which workers may feel less secure and more motivated to upskill or change how they work.[8]

Other variables pull in the opposite direction. When typical work-experience requirements are high, careers often follow more stable professional paths, and incumbent workers may face less immediate pressure to reinvent themselves.

Unions and licensing also play a role. Where union representation is strong, or where labour market entry is tightly regulated through licences and certifications, competitive pressures can be partially cushioned.[9] [10] With wage dispersion, we capture how distinctive the output of each employee is, with less dispersion indicating more labour market competition.[11] Finally, we look at the prevalence of involuntary part-time and temporary employment, which tends to signal weaker bargaining power and a more precarious position in the labour market.[12]

Taken together, these indicators give us a summary measure of how exposed an occupation is to competitive, contractual and institutional forces. A high Labour market competition score means workers are more likely to face job churn, income risk and weaker protections – all factors that, in theory, increase the incentive to adopt productivity-enhancing technologies such as AI.

7 Audoly, Richard. "Self-Employment And Labor Market Risks." International Economic Review 66.2 (2025): 661-686.
8 Davis, Steven J., and John Haltiwanger. "Gross job flows." Handbook of labor economics 3 (1999): 2711-2805.
9 VanHeuvelen, Tom, and David Brady. "Labor unions and American poverty." ILR Review 75.4 (2022): 891-917.
10 Kleiner, Morris M., and Evgeny Vorotnikov. "Analyzing occupational licensing among the states." Journal of Regulatory Economics 52.2 (2017): 132-158.
11 Autor, David, Arindrajit Dube, and Annie McGrew. The unexpected compression: Competition at work in the low wage labor market. No. w31010. National Bureau of Economic Research, 2023.
12 Kalleberg, Arne L. Precarious lives: Job insecurity and well-being in rich democracies. John Wiley & Sons, 2018.

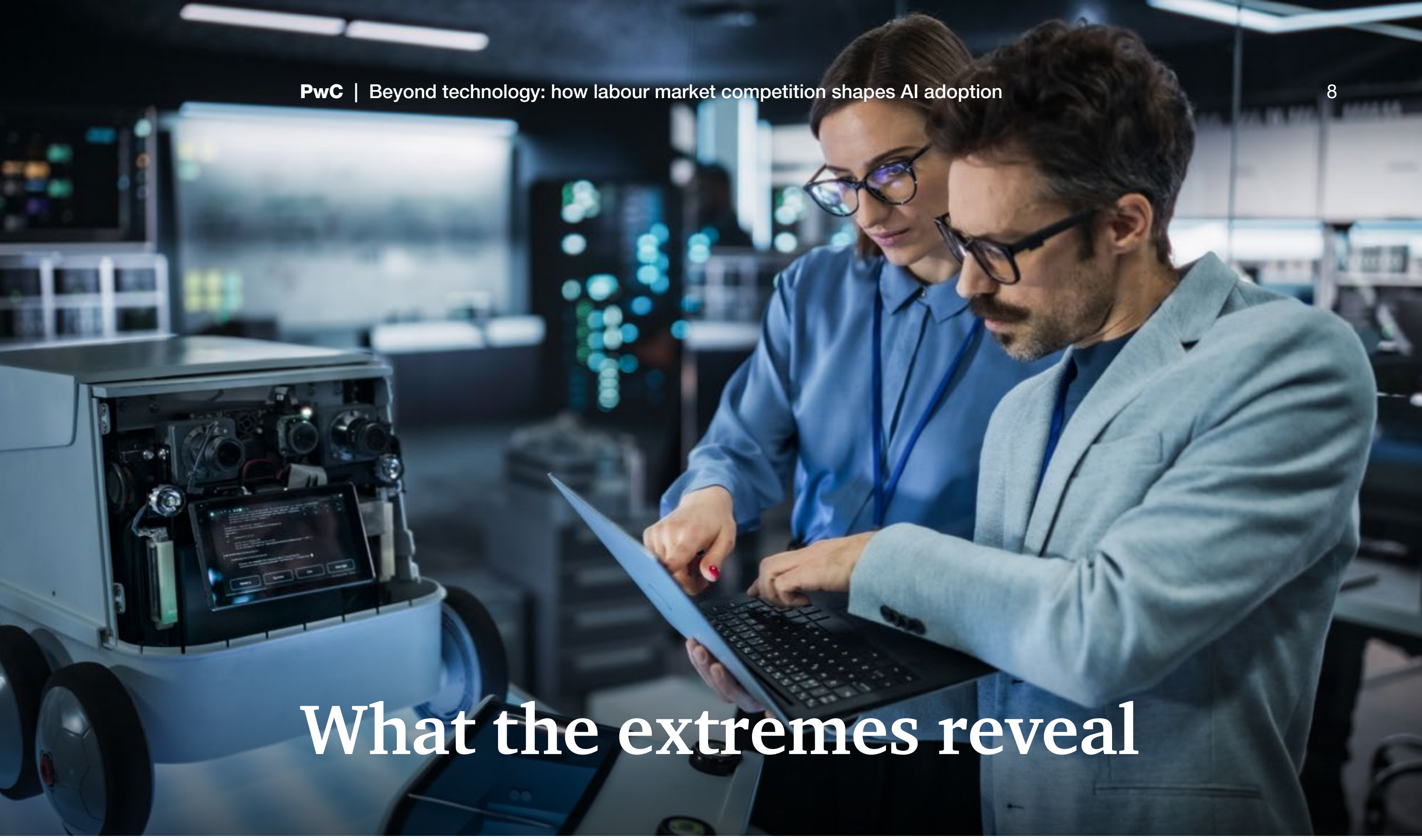
How the Labour market competition index is constructed

Our Labour market competition index is a novel measure that we build from scratch for this research. The goal is to quantify how strongly labour-market conditions push workers in different occupations to adjust the way they work, reskill or change jobs – in other words, the economic "pressure" that can interact with AI capabilities.

We select the underlying indicators based on economic reasoning and data availability, focusing on variables that are observable at the occupational level: self-employment, separation rates, wage dispersion, union coverage, licensing requirements and the prevalence of involuntary part-time or temporary work. Each of these captures a different channel through which market forces shape workers' bargaining power, job security and incentives to adapt. Wherever possible, we use data at the most granular level of aggregation; when an indicator is only available for broader occupational groups, that group value is applied to all occupations within it.

All indicators come from recognised labour-market data sources. Most are drawn from O*NET and the US Bureau of Labor Statistics, and therefore use the Standard Occupational Classification (SOC) system. There are two exceptions: involuntary part-time and involuntary temporary work, which we take from CEDEFOP data based on the ESCO classification. To incorporate these variables alongside the US data, we use an ESCO–SOC crosswalk, translating the CEDEFOP indicators into the same occupational framework as the rest of our dataset.

Because some indicators have a positive relationship with market competition and others a negative relationship, we first adjust each variable so that higher values consistently mean stronger exposure to market forces. We then standardise all indicators and take their average to obtain a single raw Labour market competition score for each occupation. This composite score is standardised once more to create the final Labour market competition index. In this index, higher values indicate occupations where competitive pressures, job churn and weaker institutional protections make workers more exposed to market forces.



What the extremes reveal

Looking at the extremes of each distribution already hints at the tension between technological potential and labour market competition.

At the very top of our Labour market competition index we find a set of largely manual and service-oriented occupations, shown in the left-hand column below. These roles tend to be characterised by relatively low job security, high turnover and limited institutional protection. Workers in these occupations are highly exposed to labour market forces. Yet many of their core tasks are physical, manual or tightly tied to on-site service, so current AI tools may have only limited direct relevance, at least in the short term.

On the other side of the distribution sit occupations that are typically embedded in formal institutions, with strong professional norms, clear hierarchies and, in many cases, regulated entry and tenure protections (right-hand column). Workers here are relatively shielded from day-to-day competitive pressure on the labour market – even when technology may be changing around them.

Top 5 occupations in Labour market competition	Bottom 5 occupations in Labour market competition
Forest and Conservation Workers	Judges
Amusement and Recreation Attendants	First-Line Supervisors of Police and Detectives
Cooks	General and Operations Managers
Farmworkers	Administrative Law Judges, Adjudicators, and Hearing Officers
Restaurant Hosts	First-Line Supervisors of Correctional Officers

If we now look at the extremes of AI exposure, we see a very different pattern. The table below summarises the occupations with the highest and lowest AI exposure scores. The roles on the left are knowledge-intensive and rich in analysis, documentation, forecasting, writing and decision support. They sit squarely in the sweet spot of current generative AI technology. The roles on the right are dominated by manual, physical or highly embodied activities, where today's AI offers far less potential to take over core tasks.

Taken together, these tables make one point very clear: **high AI exposure and high Labour market competition do not automatically coincide**. Lawyers, for example, appear at the low end of Labour market competition but have relatively high AI exposure. Many service and agricultural workers face intense labour market competition but, at least for now, relatively limited AI potential. This already suggests that AI adoption might not simply flow wherever the technology can reach; it may also reflect the underlying economic environment in which workers and employers operate.

Top 5 occupations in AI exposure	Bottom 5 occupations in AI exposure
Survey Researchers	Dishwashers
Writers and Authors	Roofers
Interpreters and Translators	Cooks
Public Relations Specialists	Athletes and Sports Competitors
Animal Scientists	Pipelayers

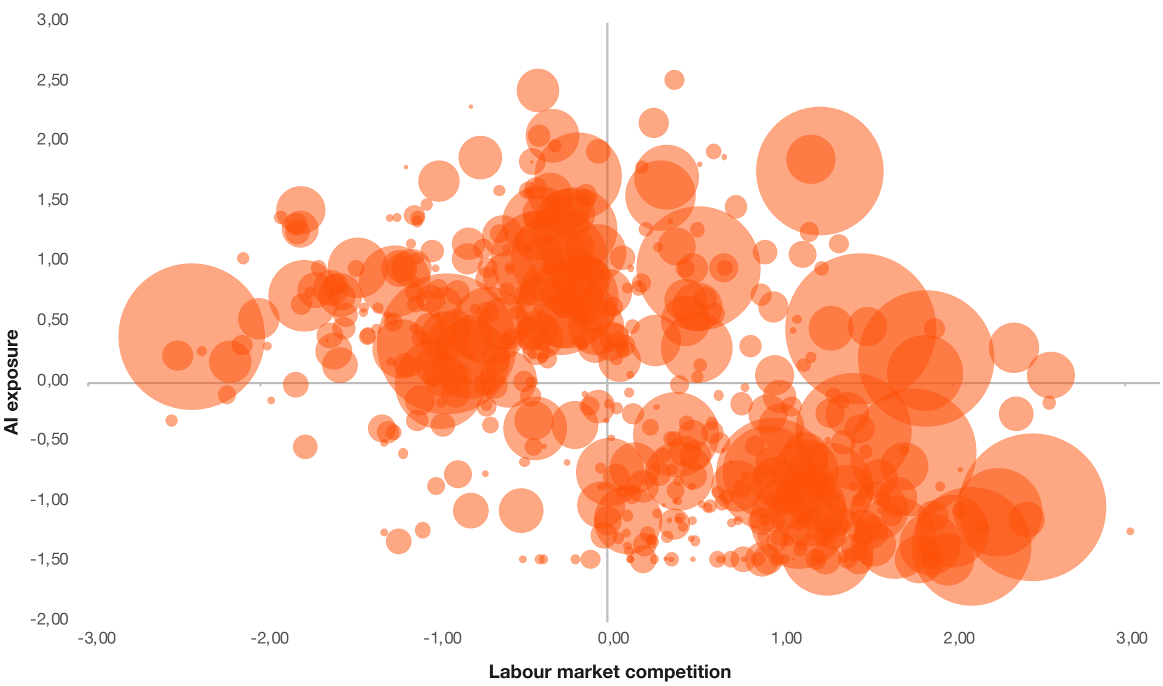
Mapping AI exposure and labour market competition

The picture becomes much clearer when we plot all occupations on a two-dimensional chart, with Labour market competition on the horizontal axis and AI exposure on the vertical axis. Splitting based on the average exposures to each creates four quadrants.

When we count how occupations are distributed across these quadrants, the pattern is striking.

Seventy-six occupations sit in the high-AI, high-Labour-market-competition quadrant. Sixty-four occupations are in the low-AI, low-Labour-market-competition quadrant. A much larger group – 212 occupations – have high Labour market competition but low AI exposure. And 257 occupations have low Labour market competition but high AI exposure.

Occupations by AI exposure and Labour market competition



Bubble sizes indicate the number of employed people on each occupation in the US in 2024

Number of Occupations in each quadrant

		Labour market competition	
		Low	High
AI Exposure	High	**212**	**76**
	Low	**64**	**257**

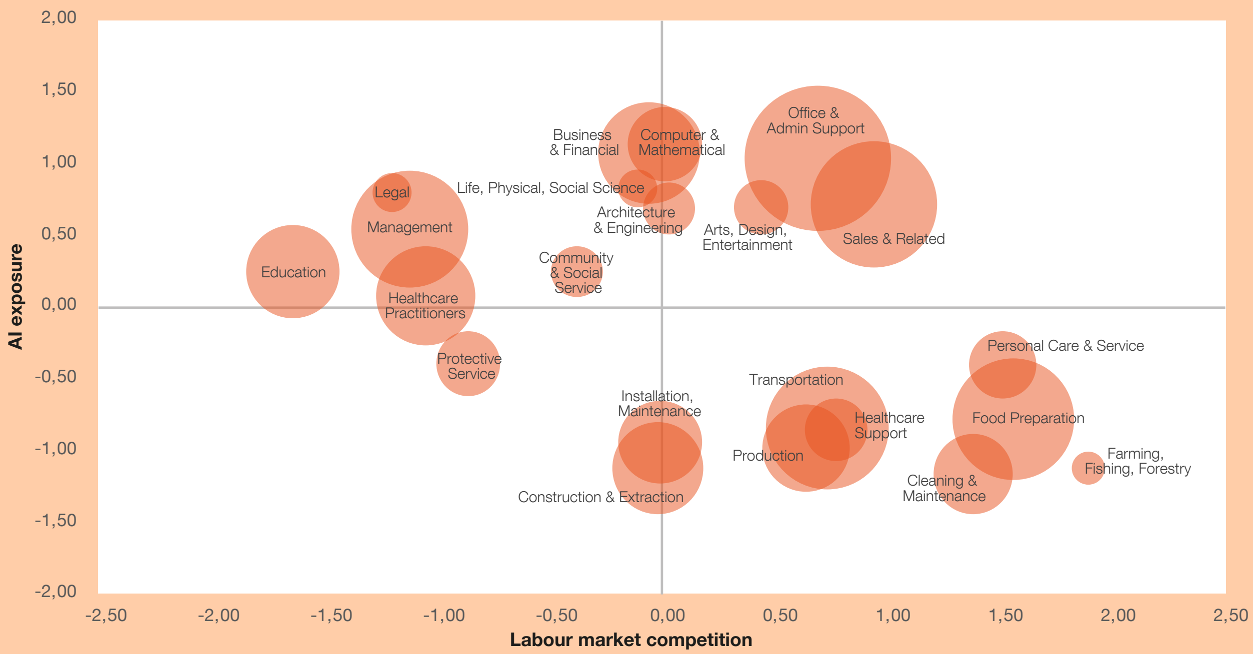
This tells us two important things. First, for most occupations where AI has strong technological potential, the "push" from market forces is not automatically present. Workers in these roles may see AI tools emerging around them, but they do not necessarily feel intense competitive pressure to adopt them quickly.

Second, in many occupations where labour market forces are intense – where job security is low and competition is fierce – AI does not yet offer a compelling technical solution for the core tasks. In those cases, economic pressure may drive other types of change first, such as shifts in business models, wage structures or staffing, before AI comes to the forefront.

In other words, AI exposure is a necessary but not necessarily a sufficient condition for adoption. The misalignment between capability and market incentives means that AI adoption will be uneven unless organisations deliberately shape the incentive environment.

AI exposure and Labour market competition by occupation group

In the chart below, we recreate the mapping, but clustering occupations by their group. We see that Office and administrative support occupations and Sales occupations are two large clusters high AI exposure and high Labour market competition. Computer and mathematical occupations have high AI exposure, but they face average Labour market competition. Food preparation and serving is another large cluster. It has limited AI exposure, but very high Labour market competition.



Bubble sizes indicate the number of employed people on each occupation in the US in 2024

Testing the link between labour market competition and AI use

Conceptually, it makes sense that stronger Labour market competition should increase the likelihood that occupations with AI potential actually adopt it. We were not expecting Labour market competition on its own to drive AI use; rather, our hypothesis was about the combination of the two dimensions. In other words, we expected that when both AI exposure and Labour market competition are high, the probability of being a top 10% user of AI should also be higher.

To test whether this intuition is supported by the data, we conducted an econometric analysis using a Logistic Regression. We focus on occupations across the AI exposure distribution and allow the effect of Labour market competition to vary with the level of AI exposure. This lets us examine not only whether market competition matters, but when it matters most.

The results support our interaction hypothesis, but with important boundary conditions. When AI exposure is too low, Labour market competition is not sufficient to push these occupations into the top tier of AI use. This is intuitive: if the underlying task content of an occupation offers very limited scope for AI, labour market competition on its own cannot generate usage because the capability simply is not there.

In the middle of the distribution, however – for occupations with AI exposure between roughly the first and third quartiles – the pattern is very different. In this range, higher Labour market competition is associated with a significantly higher probability that an occupation is a "high user" of AI in practice. Put simply, among this group occupations where AI could realistically be used, those facing stronger economic pressures are more likely to adopt it at scale.

Interestingly, this effect fades again at the very top of the AI exposure distribution. For occupations in the highest quartile of AI exposure, the marginal effect of Labour market competition on AI use is no longer statistically significant. High-AI roles will likely adopt technology organically due to sheer utility. When AI exposure becomes very high, the benefits of using the technology are so evident – in terms of time saved, quality improved or risks reduced – that a strong external "push" from labour market forces is mostly no longer needed. In these occupations, AI may become a default part of how work gets done, regardless of the underlying level of market competition.

Methodology and model specification

To empirically isolate the drivers of adoption, we employed a binary logistic regression model predicting the likelihood of an occupation falling into the top decile of our AI use index. Although here we focus on one model specification, we also used different specifications as robustness checks and to complement our findings.

The AI use index is created by adjusting the share of AI usage attributed to each occupation in the Anthropic Economic Index by the occupational employment. This way, it measures which occupations are overusing AI in relation to their size.

The regression specification tests whether the effect of labour market competition changes based on the level of technical AI exposure. We included continuous main effects to control for linear trends, alongside categorical dummy variables to test the non-linear "sweet spot" hypothesis.

The model takes the following form:

$$\text{logit}\,(P) = ß_0 + ß_1\text{Mkt}_c + ß_2\text{AI}_c + ß_3\text{D}_{midAI} + ß_4\text{D}_{highMkt} + ß_5\,(\text{D}_{midAI\ x}\,\text{D}_{highMkt})$$

Variabel definitions:

- Mkt_c, AI_c: Continuous market and AI exposure indices, centered at their means.
- D_{midAI}: A binary variable for occupations falling within the "messy middle" of AI exposure (Q25-Q75).
- $\text{D}_{highMkt}$: A binary variable for occupations facing the highest competitive pressure (Top Quartile, \$>\$Q75).

Results

The continuous main effects were both statistically significant: AI exposure ($p < 0.001$, OR=5.07) acts as a strong driver, while Labour market competition ($p = 0.02$, OR=0.67) generally dampen usage when treated as a linear trend. The individual dummy variables for the AI mid-range ($p = 0.67$) and High-competition quartile ($p = 0.72$) were not statistically significant on their own. However, the focal Interaction term was significant ($p < 0.05$), yielding an odds ration of 5.04, confirming the unique synergistic effect within this specific segment.

Taken together, these findings refine our central message. AI exposure, as a measure of technological capability, is a necessary but not sufficient condition for adoption – especially in the large group of occupations with moderate AI exposure, where labour market forces and incentives play a measurable role in turning potential into real usage. At the very low end of AI exposure, labour market competition cannot substitute for missing capability. And at the very high end, capability becomes so compelling that AI adoption happens even without a strong market "push".

For leaders, the implication is that they cannot directly control the frontier of AI capabilities – that is driven by innovation in the technology ecosystem – but they can influence the incentive and support structures within their own organisations, particularly in the broad middle of occupations where AI could realistically be used but is not yet a default.

Validity of the results for the Netherlands

The analysis in this report is largely based on data and studies from the United States. Are these results valid in the Dutch context?

AI exposure by occupation: The differences in AI exposure between occupational groups are still relevant in the Dutch context. The nature of tasks within occupations is comparable, meaning that the relative AI exposure scores are also indicative for the Netherlands. There might be some small differences on specific occupations. Lawyers, for example, have slightly different tasks under the American common law system and the Dutch civil law system. But we don't expect the impact on overall results and the aggregate findings to be relevant.

Labour market competition: Labour market competition is generally lower in the Netherlands than in the US. This is due to stronger social safety nets, a higher degree of regulation, and a greater role for collective labour agreements and trade unions.

As a result, Dutch employees might feel less direct pressure to adapt their work or embrace new technologies. Although most of our indicators to construct the Labour market force exposure index come from the US, we expect that the differences between occupations are relatively similar in the Netherlands. While the aggregate pressure might be smaller, the structural hierarchy – where some jobs face more competitive pressure than others – likely remains consistent.

Implications: The fact that the Labour market competition is likely lower in the Netherlands emphasizes the need to provide incentives and stimulate employees to use AI. Because the external "push" from market forces is weaker, leaders cannot rely on competitive pressure alone to drive adoption. Instead, they must be even more deliberate in designing internal motivators and support structures to ensure the workforce embraces the technology.

Implications for AI literacy and incentives

These findings have direct implications for how organisations think about AI literacy and workforce strategy. They confirm that there is no one-size-fits-all solution – and they also show where differentiated strategies will have the greatest impact.

Because occupations sit in very different places on the AI exposure / Labour market competition map, a single, uniform AI training programme will not be sufficient. Employees in roles with both high AI potential and strong competitive pressure experience AI very differently from those in high-AI, low-pressure roles, or in high-pressure jobs where AI has little relevance so far. Treating these groups as if they were the same risks under-investing where adoption could be transformative and over-investing where the technology is not yet ready.

Our econometric results sharpen this picture. They show that Labour market competition only increases AI use under specific conditions: not when AI exposure is very low, and not when it is extremely high, but in the broad middle where AI is relevant without yet being inevitable. When AI exposure is too low, no amount of Labour market competition can compensate for the absence of technical capability. When AI exposure is very high, by contrast, the benefits of using the technology are so evident that workers adopt it regardless of labour-market competition. The "push" from Market forces matters most in the middle of the distribution – precisely where many organisations are struggling to move from pilots to widespread, everyday use. This has three practical consequences for AI literacy and incentives.

First, in the broad middle range of occupations - where AI is capable of transforming tasks but is not yet an inevitable default - and where Labour market competition is also elevated, AI literacy and incentives are powerful levers. Here, workers can realistically use AI, but adoption is not guaranteed. Targeted interventions focused on enablement, promotion, and upskilling – such as practical training on task-level use cases, time and space to experiment, and visible recognition for early adopters – can tilt the balance.

Second, in occupations with high AI exposure but relatively low Labour market competition – for example some professional, managerial or public-sector roles – the focus should shift from external pressure to the internal value proposition. Leaders need to make the case for AI explicitly, linking it to personal benefits (freeing up time for higher-value work, improving quality, reducing routine burdens) and to organisational outcomes such as client experience, compliance or service levels. Unlike the bottom-up adoption seen in high-pressure roles, this requires a top-down approach: incentives must first articulate clearly why AI is essential for the organisation and the job, followed by literacy programs to help employees reach the required level of understanding and confidence.

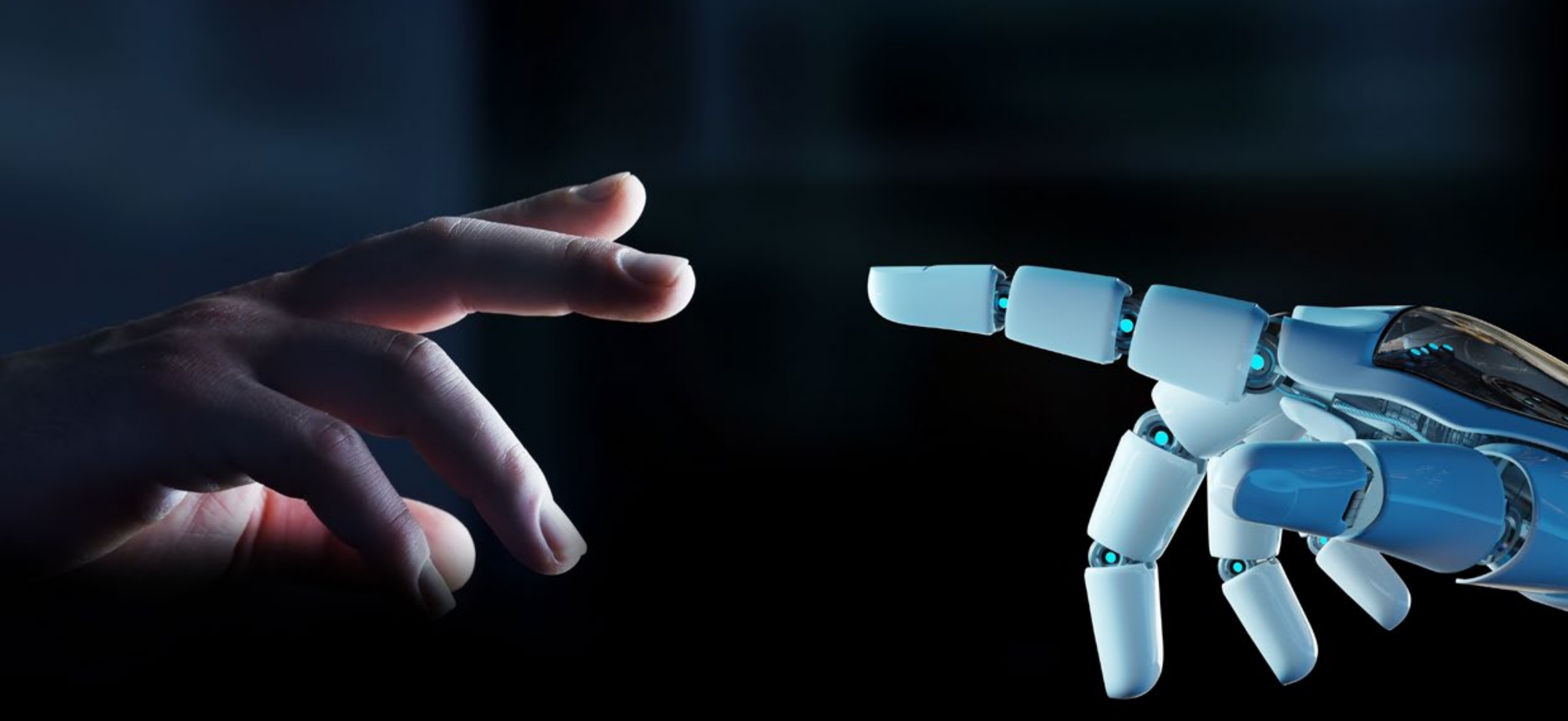
Third, in occupations with high Labour market competition but limited AI potential, the immediate priority should not be to push AI tools at all costs. If AI exposure is very low, market competition alone cannot create meaningful AI use, because the underlying capability simply is not there. For these workers, organisations should instead focus on broader upskilling, future-proofing and resilience: helping people transition as business models evolve, and ensuring that the productivity gains generated by AI in other parts of the organisation are shared fairly. Finally, providing access to generic, reliable AI applications ensures these workers can streamline the small share of tasks with AI exposure safely, while clear guidelines prevent the misuse of tools under competitive pressure.

At the very top of the AI exposure distribution – where the technology is clearly and directly relevant – the role of incentives changes again. Here, our results suggest that Labour market competition is no longer a decisive driver of whether AI is used, because the benefits are already obvious. AI literacy in these occupations is less about if AI should be used, and more about how: setting guardrails, managing risks, safeguarding quality and ethics, and embedding responsible use into everyday decision-making.

Across all of these segments, the analysis underlines that successful AI adoption relies heavily on the engagement of the individual employee. While management can drive compliance through KPIs and strict guidelines, it is ultimately the person sitting in front of the screen or on the shop floor who shapes the effectiveness of that integration. Even the best technology, deployed in the most advanced infrastructure, delivers little value if people are unconvinced, untrained or unconcerned.

From an economics perspective, this remains a story about incentives – but now with a clearer understanding of where they bite. In the broad middle of occupations with meaningful AI exposure, our results show that incentives to adopt AI are not automatically present, and that strengthening them can make a measurable difference. If organisations want to increase adoption in these roles, they need to make sure the right incentives are in place. AI literacy is one important lever: when employees understand where AI can help in their specific tasks, and feel confident that they can experiment safely, the perceived cost of trying new tools falls. When they can see how AI use links to recognition, performance, advancement or job security, the perceived benefit rises.

Designing these incentives is not just a communication exercise. It touches performance management, learning and development, leadership role-modelling and organisational design. It also requires a strong foundation of trust: transparent governance, clear policies on data and privacy, and a realistic narrative about both the opportunities and risks of AI.



Where leaders go from here

This work provides leaders with a new lens for understanding AI adoption in their organisations. They should identify where technology and incentives are aligned, where they are in tension and where the biggest gaps lie. They can identify clusters, that are particularly ripe for proactive AI literacy strategies.

From here, the next steps are practical. Organisations should recognise that different parts of their workforce will have very different starting points, needs and incentives when it comes to AI. The journey will not look the same for a call-centre agent, a finance specialist and a field technician. AI literacy, incentives and change programmes should therefore be flexible and differentiated – tailored to the realities of specific roles and contexts, rather than treating AI as a single, generic capability to be rolled out uniformly across the organisation.

AI has the potential to rewire work and shift value pools across industries. Whether that potential is realised will depend not just on algorithms and infrastructure, but on people, incentives and leadership choices. By bringing together technological capability and market forces in a single framework, this research offers leaders a way to act on that insight – turning AI's promise into adoption that is both faster and more trusted.

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