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AI-LERT: Tracking the Jobs that Never Were

EXECUTIVE SUMMARY

Four years after the launch of ChatGPT and despite close to $2.5 trillion dollars invested in data center infrastructure worldwide, the impact of artificial intelligence on aggregate labour market indicators remains elusive. There is little paradox: as outlined in our previous paper, AI's technical potential to automate tasks is substantial, with 15% to 20% of workforce task content potentially automatable in advanced economies in the coming years, but also highly uneven across occupations and industries. Its first effects on employment may therefore be difficult to detect in economy-wide statistics.

Narrowing the scope to the industries and occupations most exposed to AI, however, suggests that the first adjustments may already be under way. In the United States, employment in white-collar industries stands roughly three million jobs below its pre-pandemic trend, while annual labour productivity growth in those same industries has accelerated from around 1.5% during the 2010s to 5.5% since late 2022. Much of the adjustment appears to be taking place through recruitment, with hiring rates approaching levels last seen during major economic downturns while layoffs remain broadly in line, and sometimes below, historical norms – a labour market firing like in a boom but hiring like in a recession.

Our new forward-looking indicator, **AI-LERT (AI Labour Exposure and Recruitment Tracker)**, seeks to detect precisely these early adjustments by tracking changes in job postings. As a forward-looking measure of labour demand, job postings are likely to respond faster than employment itself, as firms can adjust recruitment needs without

immediately changing their existing workforce. Comparing occupations with different levels of AI exposure within the same industries, thereby accounting for sector-wide economic fluctuations, we find a statistically significant and widening gap between more and less exposed occupations in France. By Q3 2026, an additional 10 percentage points of AI exposure was associated with 12.4% fewer job postings relative to their pre-ChatGPT level, compared with less-exposed occupations in the same industry. Importantly, this deterioration does not appear confined to entry-level positions and extends to vacancies requiring several years of professional experience. It also ranges beyond the already well-documented IT positions and spreads to accounting, administrative and commercial functions, with even stronger recruitment adjustments through temporary employment agencies and in occupations that play a more peripheral role within their industries.

Applying a comparable methodology to Sweden and Germany, two economies with markedly different economic structures and labour markets, reveals similar patterns with estimated shortfalls of 10.2% and 10.8%, respectively, for each additional 10 percentage points of AI exposure. Although this international convergence strengthens the evidence of a broader adjustment, it neither establishes nor quantifies a causal effect of AI on recruitment. These preliminary adjustments may not only reflect the deployment of AI, but also employers' expectations of future productivity gains. This may lead them to reconsider their recruitment needs even before the technology reaches its full potential. Nevertheless, the timing, persistence and breadth of these findings suggest that something is happening – probably more than a temporary fluctuation in recruitment.

It does not necessarily imply that overall employment will decline in the years ahead. Depending on the timing and scale of job creation relative to job destruction, four trajectories could materialize:

- (1) smooth creative destruction with broadly synchronised waves of job losses and job creations, but potentially substantial transition costs in the form of income losses for displaced workers;
- (2) disruptive creative destruction with a sharp and prolonged rise in unemployment in the transition before new jobs eventually compensate for displacements;
- (3) steady attrition marked by gradual net job losses, or, finally,
- (4) “destructive destruction” characterized by insufficient job creation, leading to a lasting decline in overall employment after a period of rapid job displacement.

The outcome is far from being technologically predetermined and will be shaped by the extent of the skills mismatch between declining and emerging jobs as well as the distribution and sharing of productivity gains, hence policy choices made along the way.

SOME OF THE THINGS YOU’LL LEARN...

In France, occupations with 10pp higher AI exposure posted 12.4% fewer vacancies since ChatGPT's launch than less-exposed occupations within the same industry. p.6

Hiring pressures extend beyond entry-level roles. p.7

Peripheral functions face greater hiring pressures than core business roles. p.8

The hiring slowdown in AI exposed occupations is also observed in Germany and Sweden. p.8

From AI exposure to possible labour market impact

Four years on since the release of ChatGPT, artificial intelligence is already leaving a measurable mark on the global economy with close to $2.5 trillion invested in data center infrastructure worldwide and cumulative investment potentially exceeding $10 trillion by the end of the decade. Underpinning this unprecedented investment wave is the promise that AI could deliver substantial productivity gains across large swaths of the economy and give early-adopting companies and countries a competitive edge.

Seeking to assess AI's potential to transform labour markets from a technical perspective, our previous study suggested that this promise was not unfounded, but that the technology's automation potential was highly uneven across occupations, industries and countries[1]. Under our agentic AI scenario, some 15-20% of workforce task content could technically be automated in advanced economies in the coming years. However, this proportion ranges from 12% in construction to nearly 27% in IT services, and from just 7% in hands-on service jobs to 29% among engineers and computer specialists. Our exposure map was therefore far from uniform: AI's technical automation potential was considerably greater for cognitive and white-collar work, while occupations requiring more physical presence or interpersonal interaction remained considerably less exposed. At the same time, technical exposure did not imply that these tasks would actually be automated, nor that exposed jobs would disappear. Rather, our findings provided a map of where labour market adjustments might be expected to emerge first if firms began translating AI capabilities into hiring.

Such differences suggest that the first effects of AI on labour markets may be difficult to detect in aggregate employment statistics. Instead, they are more likely to first emerge in the occupations and industries most exposed to automation, and through slower hiring rather than outright job losses. Indeed, as long as technology's capabilities and economic returns remain uncertain **(see Box 1)**, companies may choose to hold back on recruitment before considering reductions in their existing workforce. This is precisely what we seek to investigate in this new study by introducing **AI-LERT (AI Labour Exposure and Recruitment Tracker)**, a new indicator developed by Coface and OEM to detect early signs of changes in labour demand associated with occupational exposure to AI.

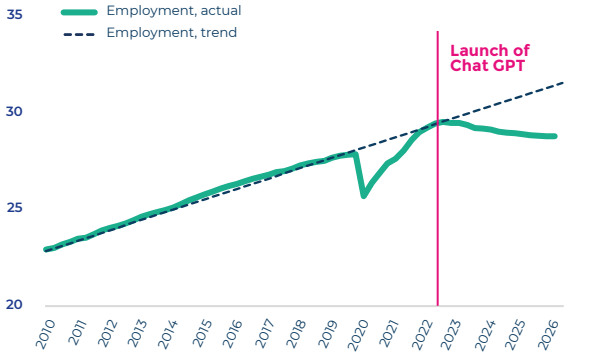
We begin by examining recent developments in productivity, employment and hiring in the United States, where AI adoption is particularly advanced and detailed economic data offer a first glimpse of how labour markets may be adjusting. We then use AI-LERT to investigate whether job vacancies have evolved differently across occupations depending on their exposure to AI, as measured by our own non-LLM-based methodology, starting with France before extending the analysis to Germany and Sweden.

Early evidence of possible productivity gains in AI-exposed industries

In the US, growing evidence of productivity growth acceleration in white-collar industries

Taken as a whole, the US labour market has so far shown no clear signs of a structural shift since the rise of generative AI tools. A closer look at the industries we consider most exposed to AI-driven automation, however, reveals a different picture, with employment and economic activity following increasingly divergent trajectories. In a broad aggregate covering information, finance and business services[5], employment peaked in late 2022 and has since declined, falling increasingly short of the trajectory implied by its pre-pandemic trend **(Chart 1)**[6]. The gap between actual employment and this historical trend now amounts to roughly 3 million jobs.

Chart 1 - Employment in US "white collar" industries *(million)*



Sources: BLS, Coface, OEM

BOX 1 - LIMITS TO THE DEPLOYMENT OF AGENTIC AI

First, these systems are opaque and therefore difficult to audit: LLM decisions are not based on readable logical rules, but on a matrix of billions of interconnected numerical coefficients (the model's "weights"). Despite progress in mechanistic interpretability, aimed at making AI decisions more intelligible, those systems remain a black box so far.

Second, they suffer from an absence of robust causal reasoning and intrinsic internal memory, making them fragile when confronted with novel situations requiring to solve out of distribution problems, whose elements are absent from training data.

Third, costs could prove too high in real-world situations, making the automation of certain tasks economically non-viable, even though technically feasible. Agentic systems indeed multiply model calls and tool interactions within complex architectures, therefore increasing the volumes of token (units of texts, such as words or fragments of words, processed by models, and used as a basis for billing certain AI services) expenditures and total costs. For example, in software engineering, agentic AI can consume 1, 000 times more tokens than recurring to simple LLM interactions (Bai et al. 2026)[2]. Anthropic itself reports that agentic AI could burn 15 times more tokens than standard conversations with chatbots[3]. Besides, the volume of tokens spent, and hence costs, are highly uncertain.

However, ongoing research into more efficient architectures could reduce costs: for instance, hybrid models combine costly conventional reasoning expressed in words with cheaper reasoning modalities operated in non-textual numerical representations ("latent space") without generating words at each step, thereby reducing token consumption[4]. Besides inference costs, hidden costs must be added (maintenance, human supervision, cybersecurity, model updates).

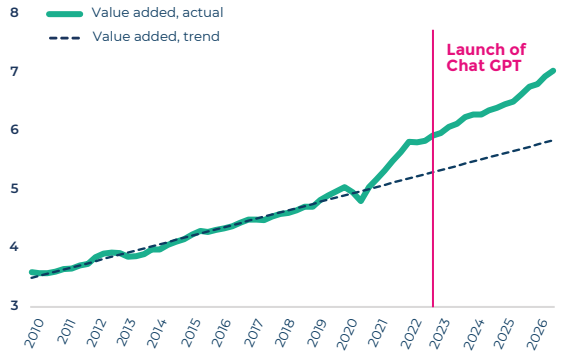
Finally, there are also serious engineering bottlenecks associated with agentic AI systems: errors could propagate in cascades through agent chains, real-time monitoring of inter-agent flows remains difficult, resource contention causes sharp performance degradations, and communication delays accumulate desynchronizations that are detrimental to operational responsiveness.

Taken together, the limitations create important operational risks and additional costs for firms.

1 - The Next Automation Frontier: a Scenario Map of AI Labour Exposure, April 2026.
2 - Bai et al. (2026), How Do AI Agents Spend Your Money? Analyzing and Predicting Token Consumption in Agentic Coding Tasks.
3 - Anthropic (2025), How We Built Our Multi-Agent Research System.
4 - Zou, J., Qi, Y., Chen, S., Bianchi, F., Zhu, S., Lu, P., He, J. & Zou, J. (2026). Hybrid Reasoning Agents.
5 - The aggregate comprises four US industries: information (including technology, media and telecommunications); finance and insurance; professional, scientific and technical services (including consulting, legal, accounting and engineering services) and administrative & support services (a more mixed bag including call centers and temporary work agency, but also cleaning services).
6 - Our analysis builds on and extends the work of Levanon (2026). Levanon, G. (2026). Three Million Missing Jobs, March 31.

By contrast, real value added across these "white-collar" industries has continued to grow and now stands well above its historical trend **(Chart 2),** suggesting that the deterioration in employment cannot simply be attributed to weaker economic activity. The resulting acceleration in labour productivity (real value added per employee) is most pronounced in the information sector, but productivity also exceeds its pre-pandemic trend across the other components of the aggregate. Interestingly, we find no evidence of a comparable acceleration in labour productivity elsewhere in the economy.

Chart 2 - Value added in US "white collar" industries *(trillion USD)*

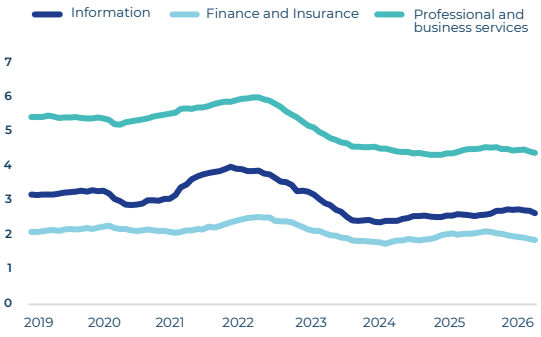


Sources: BEA, Coface, OEM

Hirings, not layoffs, bear the adjustment in employment in US white-collar industries

To better understand what is driving employment trends in these industries, we examine labour market flows, distinguishing between hires and separations (layoffs and discharges, voluntary quits and other departures). On the exit side, total separation rates remain broadly in line with their historical averages, although their composition has changed. Voluntary quits have declined substantially, especially in information and professional & business services, while layoffs and discharges remain close to historical norms (with the exception of information, where they have risen significantly). Hiring rates, by contrast, have fallen across all three industry groups since 2022 **(Chart 3)**, approaching levels last seen during the COVID-19 pandemic and the 2008-09 Great Recession.

Chart 3 - Hiring rates in US "white-collar industries", twelve-month moving average *(%)*



Sources: BLS, Coface, OEM

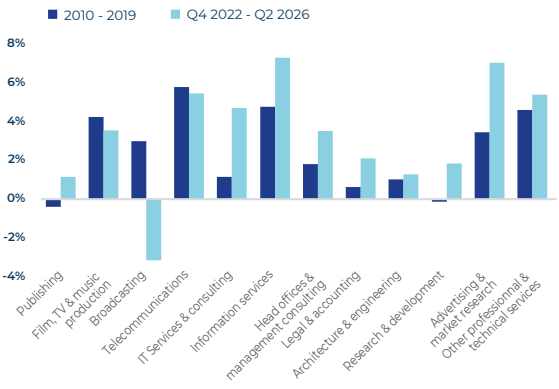
Taken together, accelerating productivity growth and declining hiring rates in otherwise resilient but AI-exposed industries suggest that firms may be adopting a wait-and-see approach by which they hold back on recruitment rather than implementing widespread workforce cuts while AI's capabilities and its returns on investment remain uncertain **(see Box 1 - Previous page)**. The information sector may already be further along in this adjustment, combining historically weak hiring and voluntary quits with elevated layoffs and discharges.

A similar, though more modest, pattern emerges in France

Are these developments specific to the United States, where AI adoption is particularly advanced, or are similar trends emerging elsewhere? France provides a useful starting point. With around 16% of workforce task content exposed to AI under our agentic scenario, the country occupied a relatively intermediate position among European economies in our previous study. Moreover, France offers reliable, relatively high-frequency labour market data and, crucially for our analysis, detailed job postings by occupation and industry. Before turning to these more granular figures, we examine whether French employment and activity data reveal a similar pattern.

Data from French statistical agencies point to a similar shift in productivity dynamics. Combining quarterly employment figures from URSSAF, France's social security contributions agency, with monthly services production indices from INSEE, we find robust growth in apparent labour productivity across most of these industries **(Chart 4),** with growth accelerating relative to its 2010-2019 trend in about two thirds of them. Much like in the US, this pattern cannot simply be attributed to declining activity: output volumes increased in all but one sector (broadcasting) between late 2022 and mid-2026. Instead, productivity gains appear largely driven by slower employment growth or outright reductions in headcount, even as production continued to expand. These estimates should nevertheless be interpreted with caution, as they rely on production rather than value added.

Chart 4 - Annual growth in production per employee by industry, France



Sources: INSEE, URSSAF, Coface, OEM

To understand whether the same pattern of lower hirings in AI-exposed industries and occupations is also visible in France and other European countries, we introduce AI-LERT, a proprietary index seeking to measure a possibly technology-related drag on new job openings.

AI-LERT reveals a widening hiring gap in AI-exposed occupations

Tracking job vacancies to detect the first signs of possibly AI-related labour market adjustments

The objective of our new Coface-OEM indicator is to detect early signs of changes in the labor market that could be related to AI adoption: AI-LERT stands for AI Labor Exposure and Recruitment Tracker. AI-LERT serves as an alert, without implying that employment effects will necessarily occur. To capture advanced signs of shifts in the labor market, we focus on job postings, therefore on labor demand **(methodology is described in Box 3[7])**.

7 - The methodology draws on the approach developed by the Federal Reserve of Dallas: https://www.dallasfed.org/research/economics/2026/0901.

Indeed, as long as AI, in particular Agentic AI, has not reached full maturity, firms may be more likely to adjust first their hiring decisions rather than layoffs. They may slow down recruitment for the occupations most likely to be automated, waiting for concrete evidence of AI capabilities before laying off employees, once the technology is mature enough and uncertainty regarding its return on investment reduced.

An indicator based on the flow of vacancies could therefore provide an early warning signal of changes in the stock of employment, potentially before these changes become visible in aggregate labor market statistics of employment levels.

BOX 2 - EARLY SIGNS OF POSSIBLY AI-RELATED LABOUR MARKET ADJUSTMENTS

Our previous study highlighted the potential of AI to reshape labour markets while emphasizing that technical exposure to automation should not be mistaken for actual job losses. With AI adoption increasing rapidly in advanced economies and researchers' expanded access to rich datasets and longer time series, a growing body of empirical research is seeking to investigate whether this technical potential is actually translating into measurable changes in labour markets.

Although the evidence is preliminary and most effects remain concentrated in some segments of the labour market, several studies find a similar pattern: the adjustment seems to be materializing mostly through weaker hiring in AI-exposed occupations, rather than through widespread layoffs. Younger workers entering the labour market appear particularly vulnerable, while the effects on aggregate employment and wages remain limited so far.

In the United States, employment among younger workers in the occupations most exposed to AI has declined in relative terms since the launch of ChatGPT in November 2022, with the gap widening over time[8]. More broadly, labour demand appears to have deteriorated in highly exposed occupations relative to less exposed ones, as suggested by evidence from Texas[9]. Importantly, the adjustment appears to operate primarily through recruitment rather than layoffs. Evidence from Canada shows that workers in the most exposed occupations have experienced a deterioration in their prospects of finding a new job, rather than an increase in job separations[10].

Similar patterns are emerging elsewhere, with younger workers appearing particularly vulnerable. Evidence from South Korea points to a form of "experience-biased technological change": AI may be more readily substituting for routine and codified tasks, often performed by younger workers, while increasing the relative value of the tacit knowledge, interpersonal and organisational skills of more experienced employees[11]. In Denmark, AI adoption has similarly been associated with slower hiring, particularly among younger and highly skilled workers, but without any statistically significant effect on overall employment or wages[12].

Evidence from France reveals a similar pattern. Beyond employment dynamics, the spread of generative AI also appears to affect the demand for specific skills. In particular, declining demand for IT skills suggests that the technology may be lowering certain technical barriers to entry and reducing the value of digital skills that were previously in high demand[13]. Using an LLM-based exposure index, Palladino et al. (2026) find that permanent hiring of workers aged 21 - 29 declined by 20 percentage points more in the most AI-exposed occupations than in the least exposed ones between November 2022 and March 2026[14].

The deterioration in hiring prospects for younger workers raises concerns that extend beyond their immediate difficulties in entering the labour market. Entry-level positions are also where workers acquire, through experience, many of the skills they will need later in their careers. Reducing recruitment today could therefore have lasting consequences for the supply of experienced workers tomorrow. This raises the risk of "impoverishing automation": when the cost savings associated with automating junior-level tasks are limited, the disruption of experience accumulation may ultimately reduce output in the long run by undermining the development of the skills required for more senior positions[15].

BOX 3 - HOW AI-LERT DETECTS EARLY SIGNS OF AI-RELATED HIRING ADJUSTMENTS

Measuring the relationship between AI exposure and recruitment

We use quarterly job postings data from France Travail, the French public employment service. Two series are provided: vacancies posted directly by employers on France Travail website (32.6% of all France Travail vacancies in Q1 2026) and a broader series that add vacancies posted on partner recruitment platforms (67.4%). We restrict our analysis to the first series. This is a conservative methodological choice aims to prevent our measures to be affected by changes in the composition or number of partner platforms over time.

Our data therefore do not include all vacancies in the French labour market.

Observations are at the occupation (ROME classification) and sector (A88 classification) level, over the period 2021Q1-2026Q3. Series are seasonally adjusted using occupation-specific quarterly seasonal factors estimated over 2015-2018.

For each quarter, the change of job postings since Q3 2022 (before the launch of ChatGPT) is compared across occupations having different levels of AI-exposure within the same sector.

We estimate a two-period conditional Poisson pseudo-maximum likelihood model, implemented as a weighted binomial specification. By conditioning on the cumulated number of job postings in the quarter considered and the reference quarter (2022Q3), we eliminate occupation and sector shocks, thereby accounting for time-invariant differences between occupation x sector cells. The specification controls for sector and time fixed effects.

Regressions are weighted by the total number of job postings across the two periods considered. Standard errors are clustered at the occupation (ROME) level.

REGRESSION SPECIFICATION:

$E[Y_{ist}|X] = \exp(a_{is} + Y_{st} + \beta_t + AI_i \cdot 1[t \neq t_o])$, where:

Y_{ist} : seasonally adjusted job postings for occupation i, sector s, quarter t.

a_{is} : occupation × sector fixed effects.

Y_{st} : sector × quarter fixed effects.

AI_i : occupation-level AI exposure, measured in percentage points.

t_o : reference quarter.

β_t : coefficient measuring the differential change in job postings associated with AI exposure, relative to the reference quarter.

X : set of explanatory variables (fixed effects and AI exposure by occupation)

AI-LERT measures the differential change in job postings associated with a 10 percentage-point increase in AI-exposition index, compared with Q3 2022 and controlling for sector specific changes.

Extending the analysis to experience requirements

We rely on the same methodology to exploit job postings disaggregated by level of experience: less than one year, 1-2 years, 2-4 years, and more than four years. For each quarter, we estimated a two-period conditional binomial model in which we include interaction with indicator variables capturing the four levels of experience required. This specification allows the relationship between AI-exposure and job posting dynamics to change with the level of experience.
We stress one important caveat. For this breakdown by experience, sectoral information is not available so that we cannot control for sector-specific shocks.

8 - Brynjolfsson, Erik, Bharat Chandar and Ruyu Chen (2026), "Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence", Stanford Digital Economy Lab, Working Paper, revised 12 August 2026.
9 - Dodini, Samuel and Tucker Smith (2026), "Job Postings Show Early Signs of AI Automation Impact", Dallas Fed Economics, Federal Reserve Bank of Dallas, 1 September 2026.
10 - Brouillette, Dany, Tatjana Dahlhaus and Gabriela Galassi (2026), "Early Signs of AI-Driven Adjustments in Canada's Labour Market", Sparks at Bank, Bank of Canada, August 2026.
11 - Han, Jinsu and Samil Oh (2025), "AI Diffusion and Youth Employment", BOK Issue Note, No. 2025-30, Bank of Korea, 18 December 2025.
12 - Darougheh, Saman, Asbjørn Klein, Andreas Kuchler and Morten Spange (2026), "Artificial Intelligence and the Labour Market: The Transition Has Begun", Danmarks Nationalbank Analysis, No. 16, 16 September 2026.
13 - Andreescu, Marie-Renée and Éric Maurin (2026), "Generative AI and the Changing Demand for Skills", Paris School of Economics Working Papers, No. 2026-27, September 2026.
14 - Palladino, M. G., Bergeaud, A., Bertheau, A., Bunel, S. & Degos, O. (2026). Exposition des métiers à l'IA générative, adoption par les entreprises et dynamiques du marché du travail en France. LIFT Working Paper 2026-02, octobre 2026.
15 - Asriyan, Vladimir, Hugo Reichardt and Sandro Shelegia (2026), "Immiserizing Automation", CEPR Discussion Paper, No. 21872, Centre for Economic Policy Research, August 2026.

We first rank occupations according to their exposure to Agentic AI automation as measured using the OEM methodology presented in our previous study (thereafter "AI-exposure"). Tasks are broken down into elementary actions (a verb, an object and a contextual element) and their technical exposure to AI is then assessed through semantic analysis. This measure does not rely on an LLM-based assessment but on human-defined semantic groups, ensuring reproducibility.

We then compare changes in job postings across occupations (using quarterly, seasonally adjusted data) relative to their level before the launch of ChatGPT in November 2022. Comparisons are made within sectors to account for possible sector-specific evolutions. In other words, **by comparing changes in vacancies across occupations with different levels of AI exposure, while accounting for sector specific trends, AI-LERT estimates whether job vacancies have grown faster or slower in occupations that are more exposed to AI since the launch of ChatGPT.**

Example: in the automotive industry, job postings for maintenance workers have increased by 20% since the launch of ChatGPT, compared with just 5% for accountants. Since accountants are more exposed to AI than maintenance workers according to our exposure scores, this difference would be consistent with higher AI exposure being associated with weaker labour demand, even when comparing occupations within the same industry.

More specifically, AI-LERT estimates are expressed to indicate how much lower (or higher) the relative growth in job postings is for an occupation with an AI-exposure score 10 percentage points higher than another occupation in the same sector. We use the increment of 10 percentage points variation because it is close to one standard deviation of the occupational exposure score. A negative AI-LERT reading therefore does not mean that job postings have decreased in absolute terms, but that they are lower than they would have otherwise been since the launch of ChatGPT. AI-LERT should be interpreted with caution as detailed below.

AI-LERT shows a widening recruitment gap between more and less AI-exposed occupations in France

Since late 2022, job postings in France have increasingly diverged between occupations with different levels of exposure to AI whereas no statistically significant relationship between occupational AI exposure and recruitment dynamics was apparent beforehand. Our calculations show that a negative relationship first emerged in Q3 2023 at around -2% and has strengthened considerably ever since, reaching -12.4% by Q3 2026.

In plain terms, **this suggests that occupations more exposed to AI are increasingly falling behind their less-exposed counterparts in terms of recruitment.** This gradual but widening gap suggests that the adjustment may still be unfolding rather than nearing completion **(Chart 5)**.

As detailed in **Box 3**, weaker recruitment in more AI-exposed occupations cannot simply be attributed to a downturn in the industries employing them, since AI-LERT compares the evolution of job postings across occupations with different levels of AI exposure within the same industry, thereby accounting for broader sectoral recruitment trends.

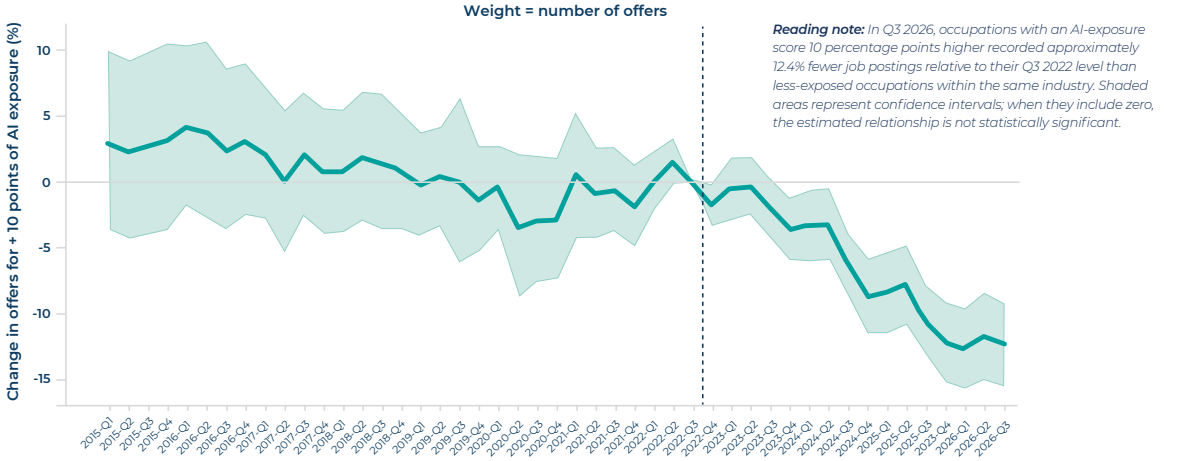
Importantly, the indicator captures a relative deterioration, not necessarily an absolute decline in job postings: vacancies in more AI-exposed occupations may have continued to grow, but at a slower pace. We stress that AI-LERT identifies a statistical correlation, not a causal relationship, and does not establish that AI itself has caused the observed divergence in recruitment. Other factors affecting AI-exposed occupations, including post-pandemic adjustments in hiring or changes in remote-working practices, may also have contributed to the trend for some occupations. Those occupation-specific characteristics should nevertheless (i) be correlated with our measure of AI exposure and (ii) have experienced a change in their effect on labor demand around the time ChatGPT was launched. While theoretically plausible, these conditions considerably narrow the range of credible concurrent explanations to AI. Therefore, the timing, persistence and growing magnitude of the relationship are consistent with AI playing a role in firms' recruitment decisions.
While we cannot isolate or quantify this contribution, AI-LERT provides an early warning signal of a possible AI-related adjustment in labour demand.

Hiring pressures extend beyond entry-level positions

Because tasks typically performed by junior employees tend to be more easily automated than those performed by more experienced workers, concerns have emerged that AI could disproportionately affect recruitment for entry-level positions - those concerns, discussed in **Box 2**, appear well-founded.

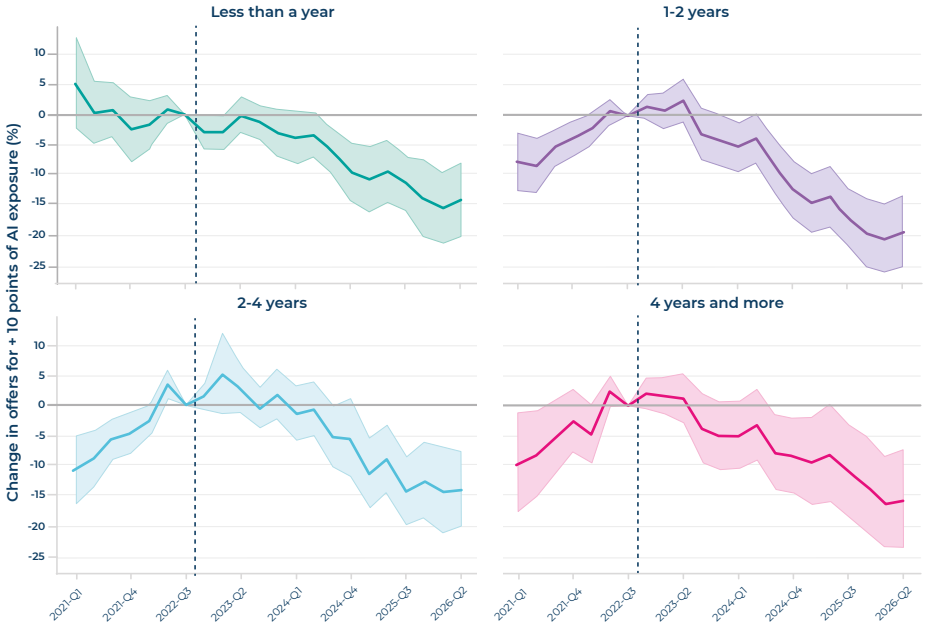
Nonetheless, our findings suggest that the emerging adjustment may be considerably broader: extending AI-LERT to distinguish job postings by the level of experience required, we find a negative relationship between AI exposure and recruitment dynamics across all experience categories, including positions requiring several years of professional experience **(Chart 6 - Next page)**.

Chart 5 - AI-LERT evolution: differential change in job postings associated with a 10-percentage-point increase in AI-exposure



Source: COFACE and OEM estimations.

Chart 6 - AI-LERT differential change in job postings by required experience level *(%)*



Reading note:
Each series shows the differential change in job postings associated with a 10-percentage-point increase in occupational AI exposure, for positions requiring the corresponding level of professional experience.

Source: COFACE and OEM estimations.

Actually, the estimated recruitment penalty is not greatest for entry-level positions: by Q2 2026, it reached -14.0% for vacancies requiring less than one year of experience, compared with -19.4% for those requiring one to two years, -14.1% for two to four years and -16.0% for more than four years. Although the differences between these estimates are not statistically significant, the results provide little support for the idea that the recruitment slowdown is concentrated only among positions requiring the least experience.

Our estimates suggest that companies may be reassessing their recruitment needs across a broader range of positions than is commonly assumed. Rather than limiting their adjustments to junior hiring, employers may also be reconsidering whether to replace departing employees or expand teams in roles requiring more experience as AI capabilities improve. While the absence of sectoral controls and the existence of pre-ChatGPT trends call for caution in interpreting these results, we believe they challenge the assumption that AI-related recruitment pressures are concentrated at the beginning of workers' careers.

Where is the adjustment most pronounced?

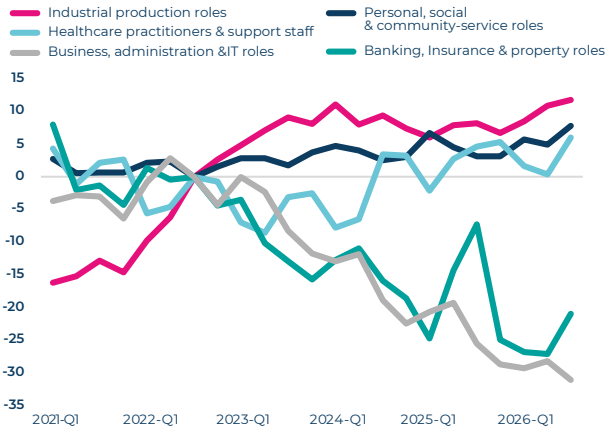
Consistent with our mapping of AI exposure which reveals substantial differences in automation (technical) potential across occupations and industries, a closer look at their respective contributions to the overall decline in job postings in France reveals a complex picture.

IT, HR, accounting and finance occupations are ahead of the trend

This is pronounced across occupational families, both in the magnitude and timing of the adjustment. By Q3 2026, job postings for business support occupations (information technology, human resources and accounting roles, in particular) as well as banking and insurance occupations were underperforming their respective sectoral trends by nearly 30%. In contrast, industrial production occupations have followed a different trajectory by outperforming their sectoral benchmarks while healthcare and personal, social and community-services roles have remained comparatively resilient **(Chart 7).** These three occupational families provide a useful counterpoint to the sharp deterioration observed in predominantly white-collar functions.

At a more granular level, the deterioration has also unfolded in successive waves. Software developers and human resources assistants were among the occupations to experience a sustained decline in relative job-posting performance from as early as late 2023. Weakness subsequently became more widespread across secretarial, administrative and accounting functions in 2024, before becoming more pronounced in sales-related occupations from 2025 onward. By Q3 2026, the latter, alongside administrative and accounting occupations, were contributing increasingly to the overall shortfall. Taken together, the shortfalls in sales, accounting, human resources, IT, consulting, legal and R&D occupations amount, compared to pre-ChatGPT trends, to the equivalent of more than 100,000 missing job postings on an annualised basis vs sector-adjusted expectations in Q3 2026.

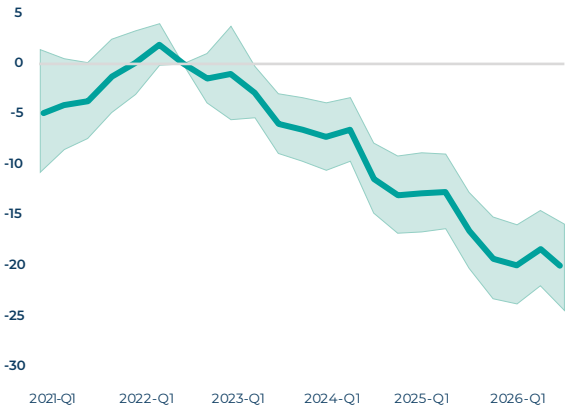
Chart 7 - Job postings by occupational family: deviation from sector-adjusted expectations in France *(%)*



Sources: France Travail, Coface, OEM

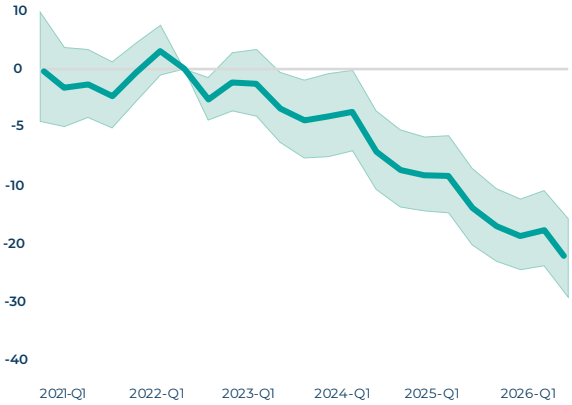
Reading note: *The chart shows the percentage deviation of job postings from the level expected if occupations within each family had followed the overall recruitment trends of their respective industries since Q3 2022. In Q3 2026, postings for business administration and IT roles were approximately 31% below their sector-adjusted expectations, while those for industrial production roles were 12% above. Negative values indicate relative underperformance, not necessarily an absolute decline in job postings.*

Chart 8 - AI exposure and job postings: estimated effect of a 10-percentage-point increase in occupational exposure in the employment services industry *(%)*



Sources: France Travail, COFACE and OEM etimations

Chart 9 - AI exposure and job postings: relative hiring performance of the 30% most exposed occupations versus the rest *(%)*



Sources: France Travail, COFACE and OEM etimations

Postings through employment agencies amplify the downward trend

Temporary employment agencies appear to have served as an important adjustment channel. Replicating our earlier calculations to measure the relationship between AI exposure and job postings in employment services companies specifically, we find that the latter exhibit a substantially stronger deterioration in demand for AI-exposed occupations **(Chart 8)** than the rest of the economy. Importantly, this difference cannot be explained solely by the occupational composition of agency recruitment. Even when comparing the same occupations across recruitment channels, the decline in agency postings remains significantly deeper for highly AI-exposed jobs. Our latest estimates indicate an additional 15% decline in relative posting odds for every 10-percentage-point increase in occupational AI exposure, compared with postings outside the employment-services sector.

The most exposed occupations carry a disproportionately high burden

Whether posted directly by employers or through employment agencies, job postings also exhibit a markedly nonlinear relationship with AI exposure. Dividing occupations into ten equally sized groups ranked by their exposure to AI reveals a striking pattern: relative posting performance deteriorates only modestly across the seven least-exposed deciles, before declining sharply among the three most exposed. By Q3 2026, the estimated shortfall reaches approximately 25% in both the eighth and ninth deciles, and 36% in the tenth, relative to the least-exposed decile. Taken together, these 30% most exposed occupations have increasingly underperformed the remaining 70% since the launch of ChatGPT **(Chart 9)**. Occupations combining strong AI exposure and substantial shortfalls in job postings include IT system administrators, HR assistants, as well as telesales and telemarketing specialists.

Data entry clerks and survey interviewers have also experienced pronounced declines, although their relative performance has improved more recently. This pattern suggests that employers may be concentrating their recruitment adjustments on occupations offering the greatest apparent potential for automation.

We also find that, among occupations highly exposed to AI, job postings have been more resilient in industries where these occupations play a relatively central role (software developers in the IT services industry, for instance) than in those where they are more peripheral to core activities (software developers in other industries)[16]. In Q3 2026, postings for software developers were 22% below sector-adjusted expectations in the IT and engineering industries, but 40% below elsewhere in the French economy. Similar contrasts emerge for telesales and telemarketing roles (-5% in the office and business service industry, -39% in the rest of the economy) or IT support and maintenance specialists (+1% in IT services, -51% in the rest of the economy). This suggests that firms may be adjusting their hiring more sharply in peripheral functions than in occupations more central to their operations.

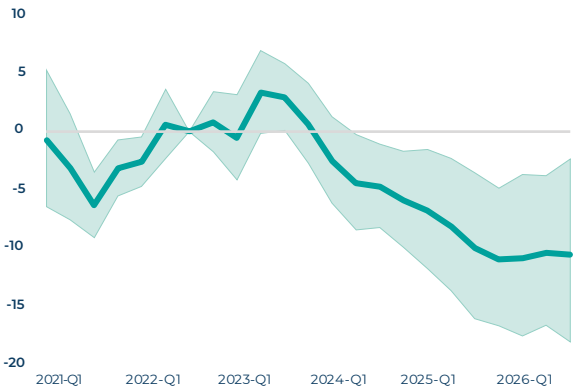
Beyond France: similar recruitment patterns in Germany and Sweden

Our findings for France call for corroboration from other countries to assess whether they reflect a broader pattern or, rather, circumstances specific to the French economy and the French labour market. Because few countries provide sufficiently detailed and consistent job postings data, in particular at the occupation-by-industry level required by our methodology, such comparisons are however difficult to draw.

Germany and Sweden are two notable exceptions in Europe, allowing us to apply an approach comparable to AI-LERT. While we intend to extend our analysis to more countries in future publications, both countries already provide a first glimpse of how the relationship between AI exposure and recruitment is evolving beyond France. These comparisons are all the more interesting given their markedly different economic and labour market structures, with Germany standing out for its industrial and engineering base and Sweden for its high concentration of IT specialists and a large social-care sector. Despite these differences, we find a similar deterioration in labour demand for occupations most exposed to AI in both countries, although the magnitude and timing differ. While differences in data coverage and occupational classifications between countries limit strict comparability, our findings suggest that the adjustment observed in France may be part of a broader trend across European labour markets.

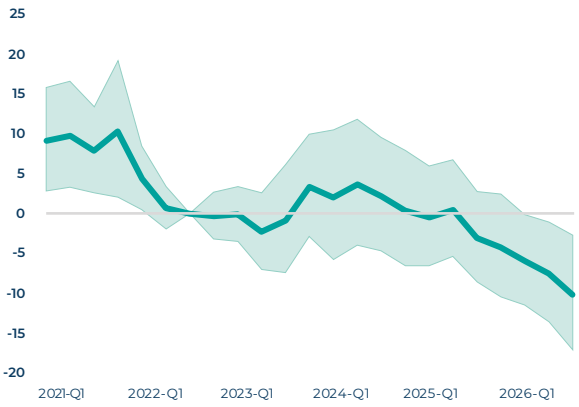
16 - We define an occupation as relatively central to an industry when a substantial share of its job postings was historically concentrated in that industry, based on pre-ChatGPT recruitment patterns (Q4 2021-Q3 2022). For instance, IT services and engineering together accounted for 63% of software developer postings before ChatGPT, compared with 43% for telesales and telemarketing positions in office and business support services.

Chart 10 - AI exposure and job postings: estimated effect of a 10-percentage-point increase in occupational exposure by AI exposure decile *(%) (Germany)*



Sources: Bundesagentur für Arbeit, OEM, Coface

Chart 11 - AI exposure and job postings: estimated effect of a 10-percentage-point increase in occupational exposure by AI exposure decile *(%) (Sweden)*



Sources: Arbetsförmedlinhen, Statistics Sweden, OEM, Coface

Germany: a similar recruitment gap, concentrated in highly AI-exposed occupations

Germany provides a broadly similar picture to France. By Q3 2026, occupations with an AI exposure score 10 percentage points higher experienced approximately 10.8% fewer job postings relative to their pre-ChatGPT level than less-exposed occupations within the same industries **(Chart 10)**.

The negative relationship emerged somewhat later than in France, before strengthening throughout 2025. Much like in France, the deterioration is heavily concentrated among the most exposed occupations, although in Germany the highest exposure decile stands out particularly sharply, underperforming the least-exposed by nearly 32%. Office and secretarial occupations account for a particularly large share of the overall deterioration, alongside administrative, accounting, telemarketing and some IT-related occupations. Employment agencies also appear to amplify the adjustment, with the estimated recruitment penalty associated with AI exposure more than twice as large in employment services (-18.5%) as in the rest of the economy (-8.7%).

Sweden: a later adjustment, partly masked by resilient social-work recruitment

Sweden exhibits a similar pattern, although the adjustment appears to have materialised later than in France and Germany. A statistically significant negative relationship between AI exposure and job postings only emerged in early 2026, reaching approximately 10.2% fewer postings for every 10-percentage-point increase in exposure by Q3 2026 **(Chart 11)**.

Looking more closely at Sweden's comparatively late adjustment, we find that its large social-work sector (NACE 88), where recruitment has remained particularly resilient, has partly masked the deterioration elsewhere in the economy. Excluding this industry reveals an earlier (Q3 2025), more pronounced (-13.3%) and statistically significant negative relationship. Interestingly, much of the deterioration is driven by the same occupations as in France and Germany: customer service representatives, telemarketers, office and accounting assistants, software developers and IT support specialists. Employment agencies also exhibit a negative relationship, although it is not significantly stronger than elsewhere in the economy.

What comes next? The forces that will shape AI's impact on employment

While AI-LERT tracks early signs of labour market adjustment through changes in job postings, the growing adoption of AI across occupations and industries, combined with its improving capabilities, could eventually prompt companies to go beyond reducing recruitment and start restructuring their existing workforce. Whether these adjustments ultimately translate into higher unemployment or are offset by the creation of new jobs remains an open question. Several factors could tip the balance one way or the other:

- **The speed and extent of automation.** The faster AI capabilities improve and the more widely the technology is deployed to replace, rather than assist, human labour, the greater the risk that job destruction outpaces the economy's ability to create new opportunities. A more gradual transition would give employees and companies more time to adjust.
- **The emergence of new tasks and occupations.** Much like previous technological disruptions, AI could generate entirely new activities and occupations. However, how quickly these will emerge, how many jobs they will create, and to what extent these new tasks will themselves remain beyond AI's reach are all open questions. The answers to these questions will determine how much of the displaced labour can ultimately be reabsorbed.
- **The response of demand to productivity gains.** By reducing production costs and potentially prices, particularly in highly competitive markets, AI could stimulate demand, expand existing markets and create new ones, supporting employment in the process. The strength of this effect will depend on the responsiveness of demand to lower prices and the labour intensity of the resulting activities.
- **The broader macroeconomic environment.** While a favourable economic environment would make it easier for new or expanding activities to absorb displaced workers, a recession could simultaneously depress job creation and accelerate automation-related layoffs, as firms facing weaker demand come under pressure to reduce costs. Previous waves of automation suggest that economic downturns can act as catalysts for workforce adjustments that firms had previously postponed.

In particular, the onset of an economic crisis, triggered by factors unrelated to automation itself, such as the burst of an AI investment bubble, could precipitate such a "disruptive creative destruction" where the mismatch between job creation and destruction profoundly disrupts the labour market[17].

- **The ability of employees and economies to adapt.** Even if enough new jobs and occupations eventually emerge, they may not be accessible to those who have lost their jobs. How quickly displaced workers can be reabsorbed into employment will largely depend on the speed at which they can retrain, acquire new skills and move between occupations, industries or regions.
- **The distribution of productivity gains.** If these gains are widely shared through higher wages lower prices or redistribution, they could support purchasing power and demand, helping to sustain employment.

However, if these gains predominantly accrue to a relatively small group of technology and/or capital owners, the resulting income concentration could weaken these compensating mechanisms, even as overall wealth increases.

Taken together, these forces could ultimately lead to very different labour market outcomes depending on two key dimensions:

- The timing of job creation relative to job destruction determines how disruptive the transition could be.
- Their relative magnitude which whether enough new jobs are ultimately created to replace those disappearing.

These two dimensions need not move together: job creation could eventually offset job destruction, but only after a prolonged period of unemployment. Conversely, new jobs could emerge relatively quickly, yet remain insufficient to replace those disappearing. Their interaction gives rise to four broad, illustrative scenarios **(Chart 12)**.

In the most favourable scenario, "Smooth Creative Destruction" would see enough new jobs emerging broadly alongside those disappearing to offset them. The transition could still entail substantial costs for displaced workers, who may lack the specialized skills required for newly created jobs or face limited opportunities to move into them. Under "Disruptive Creative Destruction", job creation would eventually compensate for job losses, but only after a potentially prolonged period of unemployment, with significant economic and social consequences.

The two remaining scenarios would pose a greater challenge to advanced economies as the problem would extend beyond the timing of job creation. Under "Steady Attrition", new jobs would emerge relatively quickly but remain insufficient to prevent a gradual and lasting decline in employment. The most adverse scenario, "Destructive Destruction", would combine rapid displacement with insufficient job creation, translating into both a disruptive transition and a lasting reduction in employment, even as productivity and overall economic output could continue to increase. These scenarios are illustrative and the early recruitment signals documented in this paper cannot predict which trajectory will prevail. Furthermore, the outcome will not be determined by technological progress alone. Education, retraining and labour market policies could help displaced workers transition to new roles, while the distribution of productivity gains through wages, lower prices or redistribution will influence the additional demand and employment these gains generate.

In more disruptive scenarios, more ambitious policy responses would be required to support those unable to find new employment, due to a permanent decline in the total number of jobs. Ultimately, whether AI delivers broadly shared prosperity or leaves a growing proportion of workers behind depends as much on economic and policy choices as on the technology itself.

Chart 12 - Four possible trajectories for AI-driven labour market adjustment

		Timing of job creation relative to destruction	
		Job creation is broadly synchronized with destruction	**Job creation is subtantially delayed**
Eventual balance between job creation and destruction	**Job creation ultimately offsets destruction**	Smooth creative destruction	Disruptive creative destruction
	Job creation remains insufficient	Steady attrition	Destructive destruction

17 - This is the hypothesis defended by the economist Gad Levanon, highlighting precedents in history: the negative impact of offshoring and automation on US manufacturing jobs was heavily concentrated around two episodes of economic downturn, the recessions of 2001 and 2007-2009. This mechanism is not confined to manufacturing: between 1990 and 2017, most (88%) of the decline in jobs in employment per capita routine cognitive and manual occupations -those most exposed to the previous automation wave- happened in windows surrounding recessions (Jaimovich, Nir, and Henry E. Siu (2020). "Job Polarization and Jobless Recoveries." The Review of Economics and Statistics, 102(1), 129-147).

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