OpenAI

The AI jobs transition framework for the EU

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From the Desk of the Chief Economist

Europe is entering a new phase of the AI transition. Across workplaces, households, firms, and public institutions, AI is beginning to change how people access information, make decisions, and get work done. For European policymakers, this raises a set of practical economic questions: which occupations and regions are likely to change first, how fast will adoption move across different sectors, and what choices can help ensure that the benefits are broadly shared? The technology is improving rapidly, but economies do not reorganize overnight. Firms need time to change processes, workers need time to adapt, and institutions need time to respond. That makes it important to hold two ideas at once: the near-term effects may be gradual, but the longer-term implications could be substantial.

At OpenAI Economic Research, we try to ground this debate in evidence as it emerges. Rather than relying only on forecasts of what AI might eventually do, we examine how people are already using the technology: the tasks they bring to AI systems, the workflows where adoption is appearing, and the early signs that may point to broader labour-market change. We also look beyond technical capability alone. Outcomes will depend on how workers use these tools, how firms redesign jobs, how education and training systems respond, and how policymakers and social partners help steer the transition.

AI's effects are unlikely to arrive everywhere in the same way or at the same pace. Some tasks may be automated, others may be augmented, and in some areas lower costs may increase demand for human work. Understanding these differences is essential if Europe is to respond with policies that are timely, targeted, and grounded in actual use.

Our goal is to make the early evidence more visible and useful. We are sharing data, developing frameworks, and contributing policy ideas to help workers, firms, educators, and governments prepare for the changes ahead. We are also continuing to build models that are more capable and easier to use, because broad access matters: the AI economy should not be shaped only by those with the most technical expertise or the greatest resources.

Since I began this role in 2024, the frontier of AI capability has moved quickly, and many early users are already reporting meaningful gains. Research comparing workplace activities with current AI capabilities suggests that the technology could affect a large share of work. Yet the aggregate labour-market evidence remains mixed, in part because adoption is mediated by organizational frictions. That unevenness should not lead to complacency. As models improve, today's limited or localized effects could become more widespread.

This report offers a framework for thinking about that transition in the European context. Instead of treating AI exposure as a single measure, we combine several considerations: the tasks AI systems can perform, the parts of work where human judgment and accountability remain central, the ways demand may change as costs fall, and the patterns of use we observe on ChatGPT. Taken together, these elements help distinguish between jobs that may be most exposed to near-term pressure, jobs more likely to be reshaped around AI, and jobs where AI could support growth.

We are launching this Framework on the occasion of my visit to Brussels and my participation in the European Central Bank Summit where I will meet European policymakers and decision-makers to explore this important topic.

I believe this work can be the starting point of a deeper conversation about Europe's preparedness to the diffusion of advanced AI, and we look forward to engaging with a broad range of stakeholders from public institutions and civil society across the EU over the coming months to discuss how to guide AI adoption, and how to ensure that its benefits reach workers, firms, and communities across the continent.

- Ronnie Chatterji
OpenAI Chief Economist

Key takeaways

01 Compared to the U.S., Europe has a smaller higher-automation-potential share and a larger reorganization share, while its less-immediate-change and growth shares are close to the U.S. benchmark. Using the AI Jobs Transition Framework across more than 2,600 ESCO occupations, our EU analysis suggests that 12% of employment is in jobs that may grow with AI, 14% of employment is in jobs with higher automation potential, 27% is in jobs likely to reorganize, and 47% is in jobs with less immediate change.

02 The EU's AI labour-market transition is likely to differ across Member States. Luxembourg, Sweden, and the Netherlands have the largest shares in occupations that may grow with AI, while Germany, Greece, and Italy have the largest employment shares in occupations classified at higher automation potential. These differences reflect different occupational structures, not national readiness, and point to the need for country-specific labour-market planning rather than a single EU-wide response.

03 AI may increase demand in some occupations as well as reduce labour needs in others. To identify occupations where lower costs could support growth, we estimate how demand for each occupation's output might respond to a 10% fall in price. Where work is digitally deliverable, discretionary, or project-based, lower costs may make new activity viable. Where work is tied to fixed caseloads, public budgets, births, shipments, or statutory service needs, lower costs are less likely to create large new demand.

04 Human involvement remains central across much of the EU labour market, but for different reasons. To understand why, we classify the dominant requirement for human delivery as physical, regulatory or accountability-based, relational, or none identified by the framework. Measured as a share of ESCO titles across 2,609 occupations, 49% are classified as physical, 28% as regulatory or accountability-based, 9% as relational, and 14% fall into a residual category where the framework does not identify a physical, regulatory, or relational requirement for human delivery. These categories describe the primary reason for continued human involvement; they are not forecasts of whether an occupation will disappear.

05 These categories are not forecasts of labour market change. Instead, we hope this framework identifies where automation pressure, work redesign, and demand-led growth may emerge, giving policymakers, employers, and training systems a common basis for preparation.

Introduction

In April 2026, OpenAI's Economic Research team released the [AI Jobs Transition Framework] for the United States. The framework maps near-term job impacts of AI in the U.S. labour market by using a methodology combining AI exposure, human necessity and demand responsiveness. Today's report adapts this framework to map near-term job impacts in the labour market across EU member states; Appendix 1 describes how the European analysis differs. The goal is not to produce a simple ranking of jobs by technical exposure, or a direct forecast of job impacts. Instead, the framework asks how AI capability is likely to interact with three additional forces: whether humans remain necessary for reasons of trust, accountability, physical presence, or regulation; whether AI changes the way work is organized rather than replacing workers outright; and whether lower costs could increase demand for a good or service enough to support employment growth.

AI capabilities are rapidly improving and spreading globally, but labour-market changes do not always reflect these developments in real time or equally across countries. The same technical capability can have different impacts depending on how work is organized, who is legally allowed to perform it, and whether services must be delivered in person. In Europe and around the world, jobs are embedded in licensing systems, professional standards, workplace rules, public-service institutions, and local patterns of demand. Those institutional details are central to understanding what AI exposure - a measure of AI's ability to complete an occupations' task - means in practice.

Applying this framework to more than 2,600 EU occupations suggests that roughly 12% of employment is in occupations that may expand if AI lowers costs and increases demand. A larger share, about 27%, is more likely to experience substantial work reorganization, as AI changes tasks, workflows, and the division of labour without necessarily eliminating the need for workers. Another 14% of EU employment is in occupations facing higher automation pressure, slightly lower than the 18% automation potential share we identified in the U.S. The remaining 47% faces less immediate change, either because the work is less exposed to current AI capabilities or because human presence, physical tasks, regulation, or institutional constraints limit near-term substitution.

These estimates should be read as a map of transition pressures, not as predictions of employment decline. The categories identify different types of adjustment: occupations where automation pressure may be more direct; occupations where workers may need to adapt to reorganized workflows; occupations where AI could raise demand for complementary human work; and occupations where near-term effects are likely to be more limited. In this sense, the framework is intended to help policymakers, employers, educators, and worker organizations distinguish between different kinds of labour-market change rather than treating "AI exposure" as a single outcome.

To extend the framework to EU member states, the analysis maps the four transition archetypes onto the European occupational structure using the official European Skills, Competences, Qualifications and Occupations ("ESCO") taxonomy and Eurostat employment data. It combines official ESCO occupation descriptions with assessments of human necessity and demand elasticity tailored to the European context. The result is an occupation-level view of how regulation, professional accountability, care, physical presence, and market structure can change the interpretation of technical AI exposure. The central message is that AI capability matters, but institutions determine much of how that capability is translated into work, wages, and employment.

> Better evidence gives workers, firms, and policymakers more time to prepare. Our role is to identify where economic change could occur and make that information widely available.

The central question: how AI capability translates into labour-market change.

Most analysis of AI and work begins with exposure: which tasks can an AI system perform? Exposure is an essential starting point, but it does not tell us whether an occupation will be automated, reorganized around a smaller set of human responsibilities, or expanded as lower costs bring in new demand. Those outcomes depend on how work is delivered and how markets and institutions respond.

Our AI Jobs Transition Framework moves beyond exposure by combining technical capability with human necessity and demand elasticity. Our framework sorts occupations into four groups: 1) jobs at higher automation potential, 2) jobs that will reorganize, 3) jobs that may grow with AI, and 4) jobs with less immediate change. The categories describe plausible near-term transition paths; they are not predictions of employment loss.

This report extends the framework originally developed in the U.S. We assign Europe-tailored human-necessity categories, demand-elasticity estimates, and direct and scale productivity effects to 2,609 ESCO occupations using official occupation descriptions, mapped task evidence, and European institutional context.

Recent European evidence reinforces the need for this more granular view. For example, [ECB analysis of 2025 SAFE]firm survey data finds that firms using AI are not, on average, reducing employment relative to non-users; firms making intensive use of AI or investing in AI are currently more likely to hire.[1]

How the framework works in the EU

The framework combines technical capability with the economic and institutional conditions that determine whether work is automated, reorganized, or expanded.

We follow the original framework as closely as possible; however, as this is an entirely different employment taxonomy and labour market environment, alterations are necessary. A direct application of the U.S. framework would implicitly assume a one-to-one correspondence between American and European occupations, employment structures, and labour-market institutions-an assumption the data do not support. The European analysis relies on ESCO and must account for variation in occupational definitions, licensing regimes, and employment composition across 27 Member States. Methodologically, we therefore treat technical exposure as the most transferable component of the framework, while re-estimating human necessity and demand elasticity using European occupational descriptions and institutional context. These Europe-specific estimates are then used to assign each occupation to its transition pathway.

Three questions organize the analysis:

- Technical exposure asks how extensively AI can perform the occupation's tasks.
- Human necessity asks whether regulation, accountability, physical presence, care, or relationships keep a worker at the center of delivery.
- Demand elasticity asks whether lower costs expand the quantity of goods and services enough to offset labour-saving productivity gains.

The occupation-level assessment then compares the mapped U.S. reference with Europe-tailored classifications based on ESCO descriptions and European institutional details.

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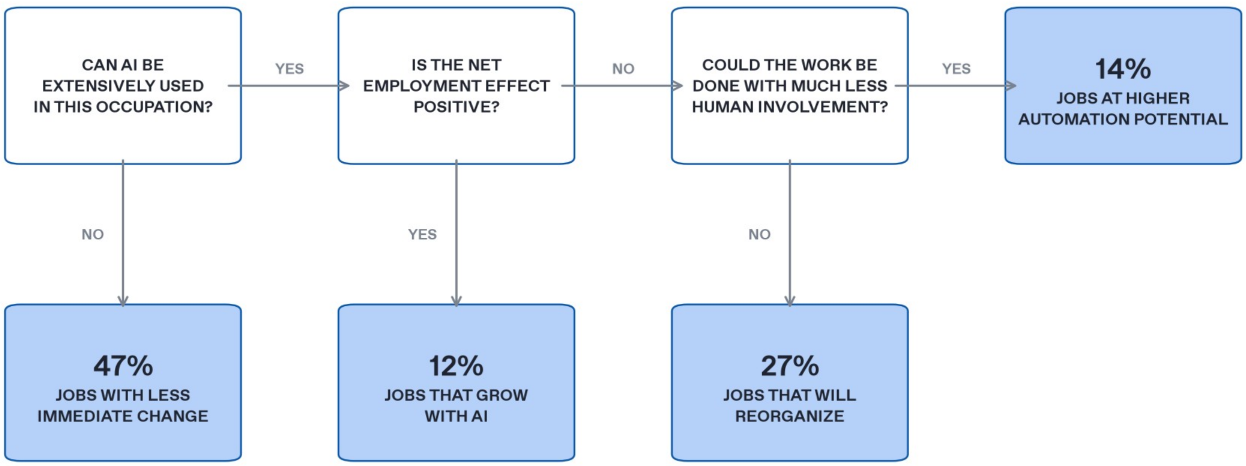
1 See Alexander Bick et al., “Mind the Gap: AI Adoption in Europe and the U.S.,” NBER Working Paper 34995 (March 2026), and the same authors’ Federal Reserve Bank of St. Louis companion article (March 30, 2026).

Framework overview

The framework maps European employment into four near-term pathways



Source: OpenAI Economic Research analysis of ESCO classifications and Eurostat 2025 employment; fractional within-ISCO-2 allocation. Note: Totals may differ from 100% due to rounding.

Where people remain necessary

AI can change a large share of an occupation's tasks without removing the need for a person to deliver the service.

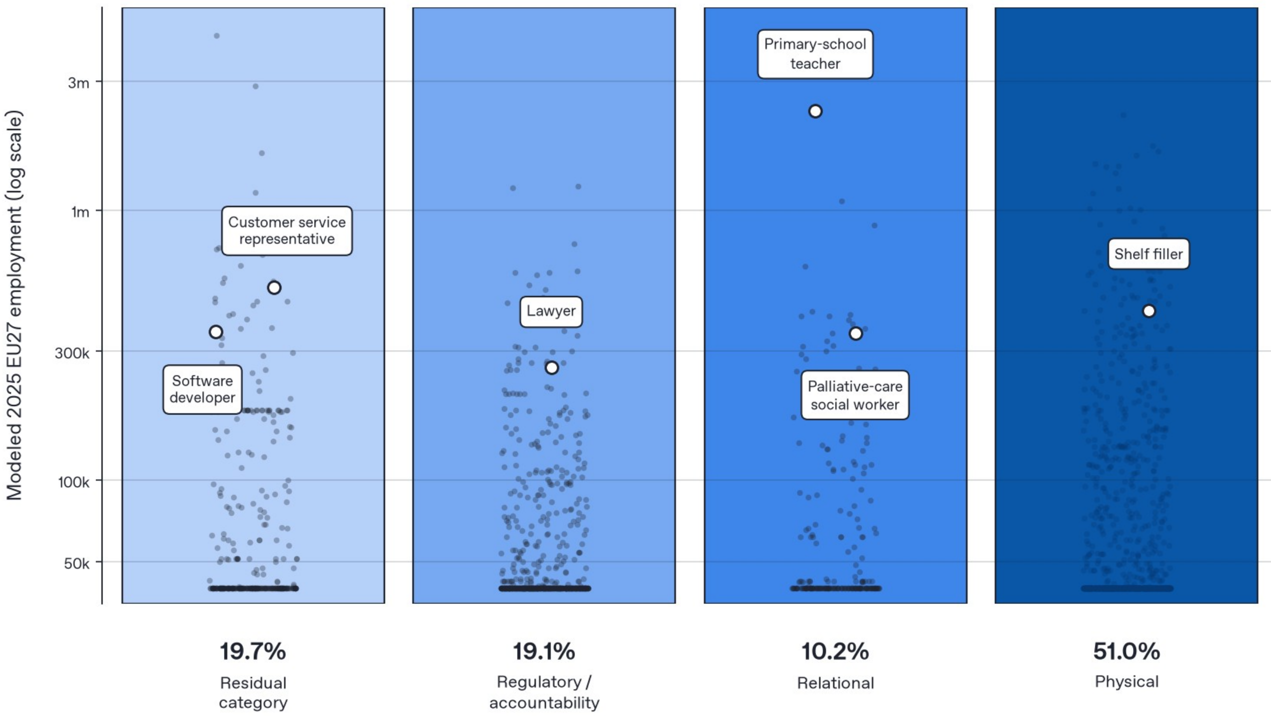
The human-delivery classification asks why a worker remains essential to an occupation's output. A person may be required to hold legal or professional responsibility, provide physical care or supervision, exercise situated judgment, or sustain a relationship that is part of the service itself. Each occupation is assigned to one final category: regulatory or accountability-based, relational, physical, or a residual category where none of those requirements is identified. Where several channels apply, physical takes priority, followed by regulatory or accountability-based and then relational. Customer preference for human interaction alone is excluded.

Across the 2,609 occupations, measured as a share of ESCO titles, 49% are classified as physical, 28% as regulatory or accountability-based, 9% as relational, and 14% fall into a residual category where the framework does not identify a physical, regulatory, or relational requirement for human delivery. The categories use information about each role to identify the primary reason a worker remains central to delivery; they do not imply that other forms of human involvement are absent.

Figure 1

Human necessity categories show why workers remain vital

Each dot is one ESCO occupation positioned by modeled 2025 European employment. Percentages are employment-weighted shares of modeled 2025 European employment.



Source: OpenAI Economic Research analysis of 2,609 ESCO occupations and Eurostat 2025 employment. Notes: If more than one category applies, priority is physical, then regulatory/accountability, then relational. ESCO employment is modeled within ISCO-2. Points below 40,000 modeled workers are shown at 40,000 for legibility; percentages are employment-weighted shares calculated from untruncated modeled employment estimates.

Teaching and clinical care both retain a central human role, but for different reasons. For secondary-school teachers, the primary category is relational: AI can help prepare lessons, assessments, or personalized materials, but instruction, classroom management, and trust still depend on a person. For general-care nurses, the primary category is physical: AI can support documentation and information synthesis, but bedside care, examination, treatment delivery, and responsibility for patient safety remain embodied. The shared result is not that the occupations are protected in the same way; it is that different parts of each job anchor continued human involvement.

European institutions directly inform these categorizations. Lawyers, linguists, and customs and excise officers fall primarily into the regulatory/accountability category because multilingual legal interpretation, border enforcement, and the exercise of public authority must remain attributable to an accountable person. Crisis social workers fall primarily into the relational category because trust and direct engagement are central, while midwives fall primarily into the physical category because care must be delivered in person, even though both roles also involve professional accountability and relationships. The category identifies the dominant reason for continued human involvement, not the only one.

Why productivity gains do not always mean fewer jobs

Whether productivity gains reduce employment depends partly on what happens to demand when the cost of providing a good or service falls.

This is a form of the rebound effect, often associated with Jevons paradox: when technology lowers the cost of producing a good or service, people may use more of it, offsetting some or, in the strongest case, all of the original efficiency gain.

Why productivity gains do not always mean fewer jobs

The demand-elasticity measure centers on the following question: if productivity gains reduce the customer price of an occupation's output by 10%, how much would the quantity demanded rise over the next two to three years? The answer helps distinguish occupations where labour-saving technology is more likely to shrink employment from those where lower costs may expand access, usage, or the number of viable projects.

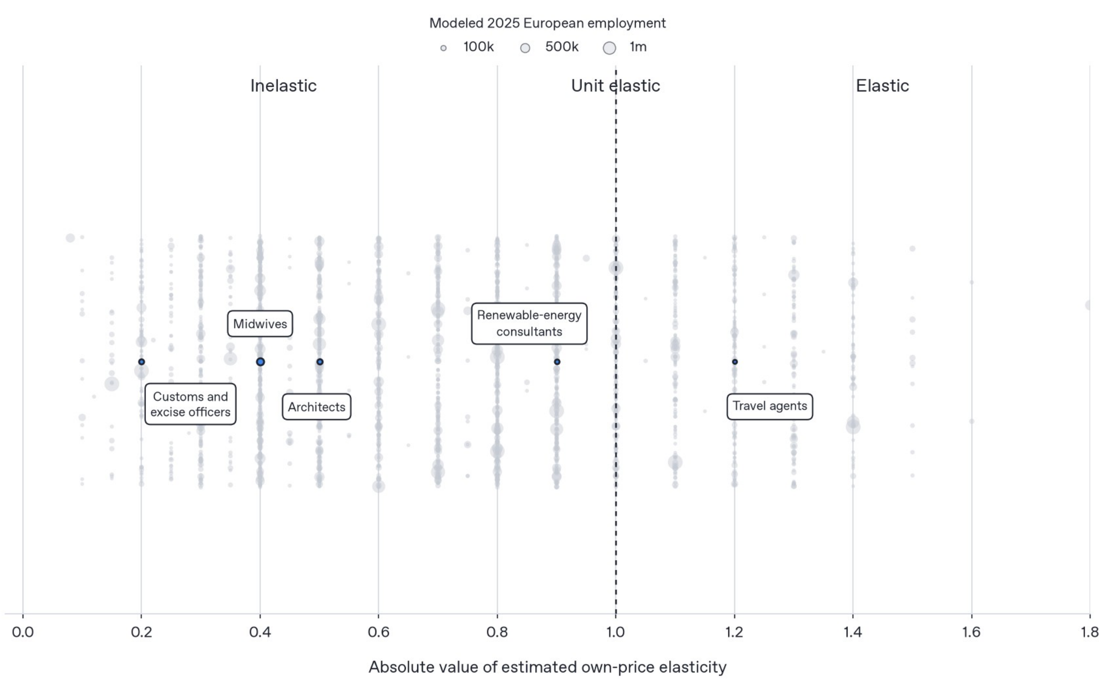
Demand tends to be more responsive where price prevents customers from buying a service, where new buyers can enter, or where lower costs unlock greater frequency. It tends to be less responsive where quantity is constrained by public budgets, physical incidence, or fixed caseloads.

We estimate the median price elasticity of a European occupation to be about 0.7. This means that a decrease in price of 10% raises output by approximately 7% (holding all else constant). On its own, that median demand response would not fully offset labour-saving productivity gains; stronger expansion is concentrated in occupations with elasticity at or above one. Demand response may remain low where service volume is tied to births, shipments, scheduled cohorts, or fixed project pipelines, because lower prices do not create many more cases. Occupations with higher elasticity estimates tend to be discretionary, project-based services, or those that can be conducted online, such as travel agents and renewable-energy consultants. In these jobs, lower prices can bring in new customers, increase purchase frequency, or make previously uneconomic work viable.

Figure 2

Europe-tailored demand response shifts at the occupation level

Many occupations are estimated to have modest demand expansion when output gets cheaper.



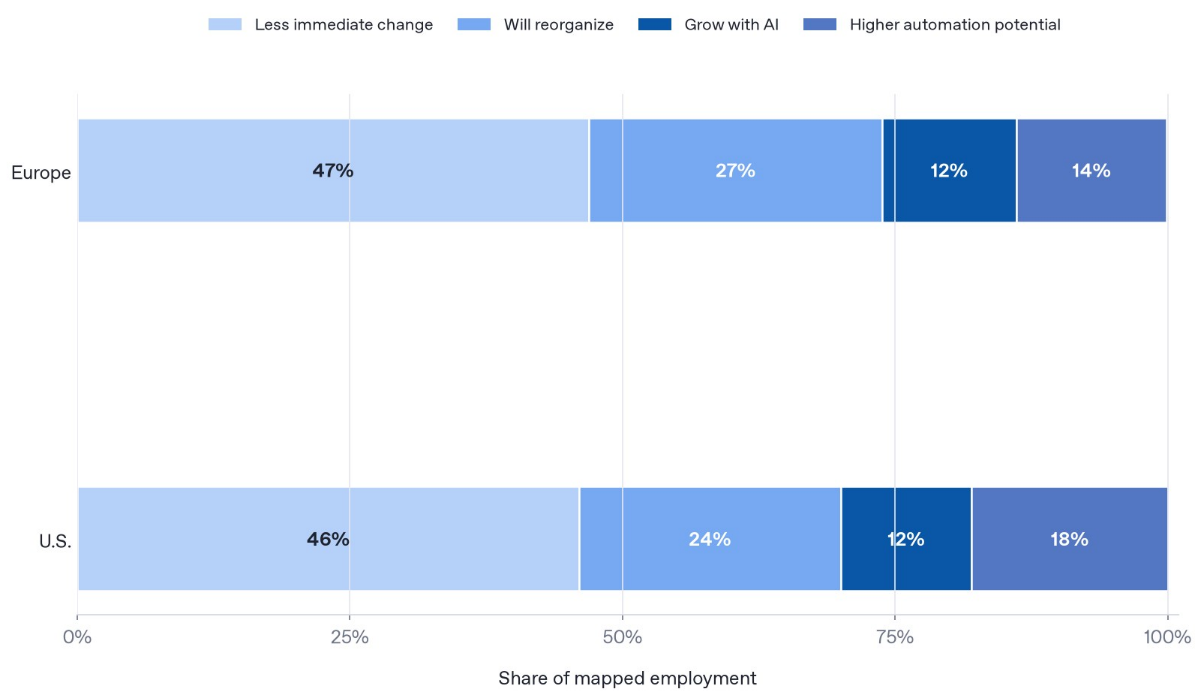
Source: OpenAI Economic Research analysis of 2,609 ESCO occupations and Eurostat 2025 employment. Each dot is one of 2,609 ESCO occupations; dot area represents modeled 2025 European employment. Estimates describe output demand, not labour demand. ESCO employment is modeled within ISCO-2; marker areas are capped at 1.5 million workers for readability.

Europe's occupational transition mix

The European framework places 14% of mapped employment in jobs at higher automation potential, 27% in jobs that will reorganize, 12% in jobs that may grow with AI, and 47% in jobs with less immediate change. The comparable U.S. report found 18%, 24%, 12%, and 46%, respectively. Europe therefore has a smaller higher-automation-potential share and a larger reorganization share, while its less-immediate-change and growth shares are close to the U.S. benchmark.

Figure 3

Share of mapped employment by transition archetype.



Source: Europe-tailored fractional within-ISCO-2 benchmark and comparable U.S. report shares. Note: Totals may differ from 100% due to rounding.

Europe's smaller higher-automation-potential share does not imply insulation from AI-driven change. Rather, it reflects the region's occupational mix. More European employment enters the reorganization path than in the U.S. benchmark, while the less-immediate-change and growth shares are broadly similar.

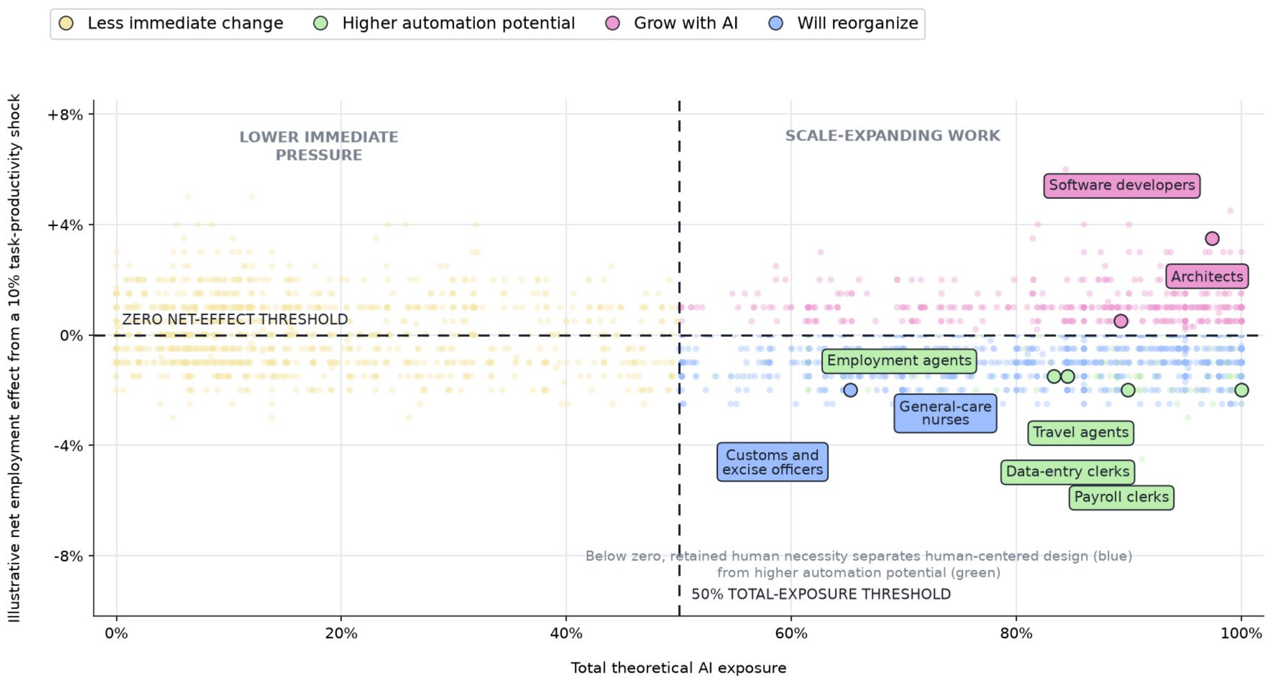
To start, Europe employs relatively more people in manufacturing, skilled trades, transport, care, education, and public-service occupations, where work is often place-based, physical, or tied to relatively fixed service volumes. The U.S. has relatively more employment in managerial, sales, and digitally deliverable business-service occupations, where AI-enabled cost reductions may make it easier to serve additional customers or expand the number of viable projects. These structural differences help explain Europe's larger reorganization bucket and smaller higher-automation-potential bucket, while its less-immediate-change and growth shares remain similar. They are starting conditions rather than fixed outcomes: sectoral growth, investment, adoption, and changing business models could shift the composition over time.

What this means

Figure 4

Classification cutoffs partition the European occupation space

European occupations split by whether estimated scale effects offset direct labour savings. Dashed lines show the 50% total-exposure threshold and the zero net-effect threshold used in the framework.



Source: OpenAI Economic Research analysis of ESCO occupations and the AI Jobs Transition Framework.

Figure 4 applies the framework's decision sequence, plotting technical AI capability against the estimated net employment effect-the direct effect plus the scale effect-of a 10% increase in effective productivity of AI-exposed tasks. Occupations below the 50% total-theoretical-exposure cutoff fall into lower immediate pressure. Above the cutoff, a positive net effect indicates scale-expanding work. High-human-necessity occupations and low-human-necessity occupations with an ambiguous small decline from -0.5% (inclusive) to 0% (exclusive) move toward human-centered redesign; the remaining nonpositive, low-human-necessity occupations face higher automation pressure.

Table 1

Selected European occupation examples

Institutional channel	ESCO occupation	Human necessity category	Demand response	Interpretation
Employment decisions	employment agent	Residual category	Inelastic	Greater automation pressure
Teaching	literature teacher at secondary school	Relational	Inelastic	Human delivery remains central
Clinical care	nurse responsible for general care	Physical	Inelastic	Human delivery remains central
Legal accountability	legal guardian	Regulatory	Inelastic	Accountable human role
Public-service access	crisis situation social worker	Relational	Inelastic	Human delivery remains central
Customer service	customer service representative	Residual category	Unit elastic	Greater automation pressure
Travel planning	travel agent	Residual category	Elastic	Lower prices expand demand
Renewable-energy advice	renewable energy consultant	Residual category	Elastic	More projects become viable

Employment decisions. Employment agents combine information work with compliance advice, negotiation, and decisions that can affect pay, classification, and workplace rights. AI can support search, matching, and drafting, and the model does not identify a strict regulatory, relational, or physical requirement for human delivery.

Teaching. A secondary-school literature teacher may use AI to prepare materials, generate exercises, or support feedback. The occupation nevertheless depends on live instruction, classroom discussion, supervision, safeguarding, and responsibility for assessment. The European occupation description makes those human duties more visible than a task list focused on content production alone.

Clinical care. Nurses responsible for general care are licensed professionals with direct responsibility for patient safety, assessment, medication, and care planning. AI can reduce documentation and information-processing burdens, but bedside care, physical execution, and clinical accountability remain central to the service.

Legal accountability. A legal guardian bears formal fiduciary responsibility for another person's welfare and decisions. AI may assist with records or analysis, but the role requires an accountable decision-maker and sustained judgment on behalf of a vulnerable person.

Public-service access. Crisis social workers provide real-time counseling, risk assessment, safeguarding, and coordination across services. AI may assist with triage or documentation, but the occupation remains shaped by situated judgment, responsibility for escalation, and direct work with people in vulnerable circumstances.

Country-level transition patterns

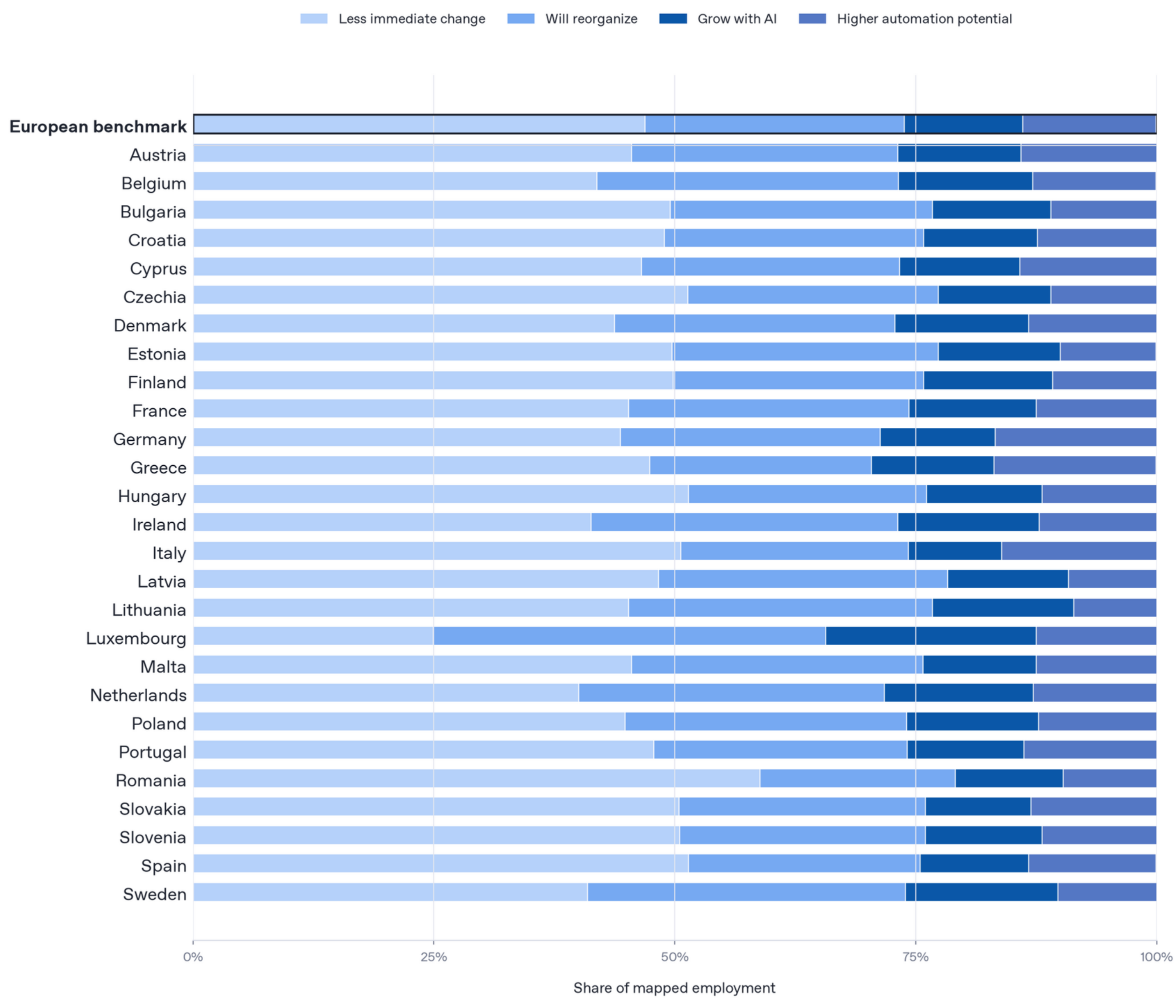
The EU-wide result is an average across countries with different occupational structures and therefore different transition challenges.

Country shares vary because observed employment is distributed differently across occupations. The same within-ISCO-2 allocation is applied to every Member State, so the chart reflects occupational composition rather than national institutional differences. A country with more employment in clerical or production roles likely has a different near-term potential profile from one with more professional, care, or digital-service employment. These figures describe the composition of potential transition; they do not rank countries by readiness and they do not forecast unemployment.

Figure 5

Transition shares differ across member states

Countries are listed alphabetically for easy lookup.



Source: Europe-tailored ESCO labels fractionally allocated within ISCO-2 and weighted with Eurostat 2025 employment. Note: The same within-ISCO-2 allocation is applied to every Member State, so country differences reflect observed ISCO-2 employment composition rather than national institutions. Rows may differ from 100% due to rounding.

Variation is uneven across the four categories: less immediate change spans 24.9% to 58.8% of mapped employment across Member States, while work likely to reorganize ranges from 20.3% to 40.7%. Higher automation potential ranges from 8.7% to 16.9%, and the share of work that may grow with AI ranges from 9.7% to 21.9%. Luxembourg, Sweden, and the Netherlands have the largest shares in occupations that may grow with AI. Germany, Greece, and Italy have the largest employment shares in occupations classified at higher automation potential. The contrast reflects differences in occupational structure and therefore in the likely mix of adaptation needs, from workflow redesign and reskilling to bottleneck management and demand expansion. These comparisons do not measure preparedness, adoption speed, or institutional quality.

Table 2
Country transition shares

Country	Less immediate change	Will reorganize	Grow with AI	Higher automation potential
European benchmark	**47%**	**27%**	**12%**	**14%**
Austria	46%	28%	13%	14%
Belgium	42%	31%	14%	13%
Bulgaria	50%	27%	12%	11%
Croatia	49%	27%	12%	12%
Cyprus	47%	27%	13%	14%
Czechia	51%	26%	12%	11%
Denmark	44%	29%	14%	13%
Estonia	50%	28%	13%	10%
Finland	50%	26%	13%	11%
France	45%	29%	13%	13%
Germany	44%	27%	12%	17%
Greece	47%	23%	13%	17%
Hungary	51%	25%	12%	12%
Ireland	41%	32%	15%	12%
Italy	51%	24%	10%	16%
Latvia	48%	30%	13%	9%
Lithuania	45%	32%	15%	9%
Luxembourg	25%	41%	22%	13%
Malta	46%	30%	12%	13%
Netherlands	40%	32%	16%	13%
Poland	45%	29%	14%	12%
Portugal	48%	26%	12%	14%
Romania	59%	20%	11%	10%
Slovakia	50%	26%	11%	13%
Slovenia	51%	26%	12%	12%
Spain	51%	24%	11%	13%
Sweden	41%	33%	16%	10%

Note: Rows may differ from 100% due to rounding.

Implications for policy and research

The framework is most useful as an early-warning and planning tool, not a job market forecast. It aims to add nuance to the conversation about the impact of AI on the labour market: which occupations are likely to face which kinds of transition, and what institutions need to be ready? Aggregate employment data will reveal major adjustment only after firms, workers, and institutions have already begun to change. That is why we strongly believe that Europe should already anticipate and prepare for these changes, in order to maximise the benefits AI will bring to businesses and society.

Across the 27 Member States, at local, national and EU levels, Europe has strong occupation, training, vacancy, and official statistical systems. The opportunity is to connect them early enough to identify where transition pressure and opportunity are emerging.

Building on this framework, governments and relevant stakeholders should focus on a few directional principles that will contribute to improving Europe's resilience. First, policy and business interventions should be designed with workers at the center, using their practical knowledge of how jobs are actually changing and can benefit from AI. Second, the EU should expand the AI Observatory announced under the Apply AI Strategy to build live labour-market intelligence that connects occupation, skills, vacancy, wage, training, and worker-flow data to identify transition pressures early. Third, Member States should translate these signals into national readiness plans that link AI adoption, skills, public employment services, social dialogue, and flexicurity-style support. Fourth, work adaptation support should be targeted where the framework and national readiness plan point to likely reorganization or higher automation pressure, with portable skills, work-compatible training, career guidance, and income support where needed. Fifth, basic AI literacy should become a universal foundation so all workers can understand, use, question, and benefit from AI. Finally, governments, businesses and academia should support pilots and empirical research to learn which interventions actually improve earnings, mobility, job quality, and shared productivity gains, including topics like:

- Which early indicators - AI use, vacancies, wages, hours, training participation, or worker flows - best predict occupational change?
- How do national regulation, collective bargaining, and service-delivery models affect AI adoption within the same occupation?
- When AI lowers the price of an occupation's output, how much additional demand and employment follows, and over what period?
- Which training and transition-support models improve earnings, mobility, and job quality for workers in occupations likely to reorganize?

The above ideas are preliminary and designed as a starting point for deeper research and policy conversations about AI and the labour market in Europe. They should be read as an invitation to policymakers, economists, social partners, employers, workers, public employment services, and civil society to explore how Europe can prepare for the Intelligence Age.

Over the coming months, we will expand and build out these ideas into concrete policy recommendations through engagement with stakeholders at both national and EU levels, with the goal of identifying practical ways to ensure that AI supports prosperity and progress across Europe.

Conclusion

This report reinforces the central finding of the original U.S. AI Jobs Transition Framework: technical capability alone does not determine labour-market outcomes. Exposure matters, but an occupation's near-term path also depends on whether human involvement remains necessary, whether lower costs expand demand, and whether organizations use AI to substitute for workers, complement them, or redesign work around them.

European institutions make these mechanisms especially clear. The same AI capability may operate differently when work is shaped by professional licensing, public budgets, statutory service obligations, multilingual access requirements, or human relationships that are part of the service itself. These factors are not peripheral. They shape how quickly tasks change, which responsibilities remain human, and whether productivity gains translate into fewer workers, more output, or new forms of work.

This report provides a reproducible European benchmark and an occupation-level assessment of how institutional context changes the interpretation of AI exposure. It should be read as a map for preparation, not a forecast. The categories identify where human responsibility is likely to remain central, where work may reorganize, and where lower costs may expand demand.

The report also offers preliminary ideas for public and private institutions working on AI and jobs. Over the coming months, we will expand and build out these ideas through engagement with stakeholders at both national and EU levels, with the goal of identifying practical ways to ensure that AI supports prosperity and progress across Europe.

Appendix 1: Methodology

Employment-weighted European comparison

Eurostat 2025 supplies employment for employed people aged 15-74, total sex, at ISCO-08 two-digit level. To construct the within-group prior, each mapped O*NET occupation's 2024 employment is allocated across its linked ESCO occupations. The allocated amounts are summed for each ESCO occupation and normalized within ISCO-2 to estimate the category shares represented in that group. Eurostat employment for each ISCO-2 group and geography is then multiplied by those category shares and aggregated. If no link is found, the ESCO occupations in that group receive equal weights. The method preserves observed Eurostat two-digit totals but does not observe the true distribution across detailed ESCO occupations. The same within-ISCO-2 prior is applied to each Member State, so country differences reflect observed ISCO-2 employment composition rather than country-specific within-group occupation mixes or institutional rules.

A country-level validation using final 2023 employment counts from Statistics Finland table 115q tested this allocation at the ISCO-08 four-digit level. Replacing the modeled within-ISCO-2 distribution with Finland's observed ISCO-4 mix, while holding Finnish ISCO-2 totals fixed and retaining the model only within ISCO-4, changed no transition category by more than 0.85 percentage points.

Occupation-level European estimates

The occupation-level universe contains all 2,609 ESCO occupations linked through the official crosswalk. Technical exposure is available for 2,473 occupations through at least one mapped O*NET occupation. The remaining 136 occupations retain missing technical exposure and are explicitly left without a transition archetype; they are not imputed into an occupation-level category. The 2,473 covered occupations feed the ISCO-2 employment aggregation described above. Counts of ESCO titles and modeled employment shares are different quantities: occupation-count summaries weight each ESCO title equally, while headline labour-market results use the modeled employment allocation.

Crosswalk and mapping

The official ESCO-O*NET crosswalk contains 4,253 links: 4,210 occupation-to-occupation links connecting 940 O*NET-SOC occupations with 2,609 ESCO occupations, plus 43 direct ISCO targets that are not used for occupation-level estimates. Among the 4,210 occupation links, 498 are exactMatch, 227 narrowMatch, 1,432 closeMatch, and 2,053 broadMatch; each ESCO occupation has between one and 20 mapped O*NET occupations (median one). The analysis uses match weights of 1.00, 0.90, 0.80, and 0.70 for exact, narrow, close, and broad links. Technical exposure and mapped task evidence aggregate covered O*NET sources using these weights, and the employment prior allocates each O*NET occupation's 2024 employment across linked ESCO occupations in proportion to them.

Demand and productivity provenance

For the headline results, output-demand response is independently estimated for each ESCO occupation using the U.S. report's demand-only generator adapted to ESCO occupations and European purchasing context (estimator version europe-demand-elasticity-us-comparable-1.0.0). The standardized counterfactual holds quality and product scope constant and asks how much more output purchasers would buy over the next two to three years after a 10% purchaser-facing price decline. The estimate excludes AI exposure, licensing, worker supply, human necessity, and technical substitutability. It is not blended with mapped U.S. occupation scores or calibrated to U.S. or aggregate European category-share targets.

A separate productivity-effects pass (estimator version europe-productivity-effects-us-production-1.0.0) evaluates a 10% increase in effective productivity of AI-exposed tasks. It estimates the direct change in labour required at fixed output and the scale effect associated with lower effective costs or prices, faster delivery, improved quality, expanded access, and new use cases; the illustrative net employment effect is the sum of the two components. Pass-through from productivity to purchaser prices is not separately observed, so these fields are structured model-based priors rather than observed or causal employment estimates. Reproducibility requires retaining the exact prompts, model snapshot, estimator versions, run dates, response identifiers, and run manifest with the occupation-level output.

Appendix 2: Classification approach

The transition classification uses the technical-exposure, human-necessity, demand-response, and productivity estimates described above. It first applies a 50% cutoff to match-quality-weighted total theoretical exposure. Among exposed occupations, positive net effects are classified as “Grow with AI”; nonpositive cases are split by retained human necessity into reorganization or higher-automation-potential pathways.

The cutoff best preserves the U.S. low- versus higher-exposure classification under O*NET-to-ESCO mapping. It is not a literal transfer of the U.S. report’s 15-hour reference: European task-time infrastructure is less complete, and 15 hours represents a larger share of work time where standard working weeks are shorter, so the U.S. percentage is not transferred directly.

Caveats and interpretation

These results should be read as a map of plausible near-term transition pressures, not as a forecast of job losses or unemployment. An occupation's classification identifies the dominant mechanism in the framework; it does not imply that every task, worker, employer, or region will experience the same outcome.

The occupation-level estimates depend on mappings among ESCO, ISCO-08, and O*NET and on the fractional allocation of Eurostat employment within broad occupational groups. Those mappings introduce measurement uncertainty, especially where descriptions are broad, occupations are heterogeneous, or crosswalk matches are indirect.

Human necessity, demand response, and the direct and scale employment effects are model-based estimates derived from occupational descriptions and structured assumptions. They are not observed causal estimates of adoption, productivity, prices, employment, or wages. Unlike the U.S. analysis, the European extension does not validate the classifications against Europe-specific realized AI-use data.

Country differences primarily reflect current occupational composition. They should not be interpreted as rankings of AI adoption, institutional readiness, policy quality, or future economic performance. Small differences between countries or categories should therefore be treated cautiously.

Actual outcomes will depend on the pace and form of adoption, organizational choices, investment, worker and firm responses, regulation, training systems, and product and labour demand. The framework is most useful as a basis for monitoring and preparation and should be updated as better evidence becomes available.

Sources

- OpenAI Economic Research, The AI Jobs Transition Framework
- ESCO classification downloads
- ESCO-O*NET crosswalk documentation
- Eurostat EU Labour Force Survey microdata
- Directive 2005/36/EC on recognition of professional qualifications
- Official EU languages
- European Observatory on Health Systems and Policies, Payment mechanisms
- European Commission, Public Service Obligations (PSOs)
- European Commission, Single market for services
- Bick, Alexander, Adam Blandin, David J. Deming, Nicola Fuchs-Schündeln, and Jonas Jessen, Mind the Gap: AI Adoption in Europe and the U.S., NBER Working Paper 34995 (March 2026)
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