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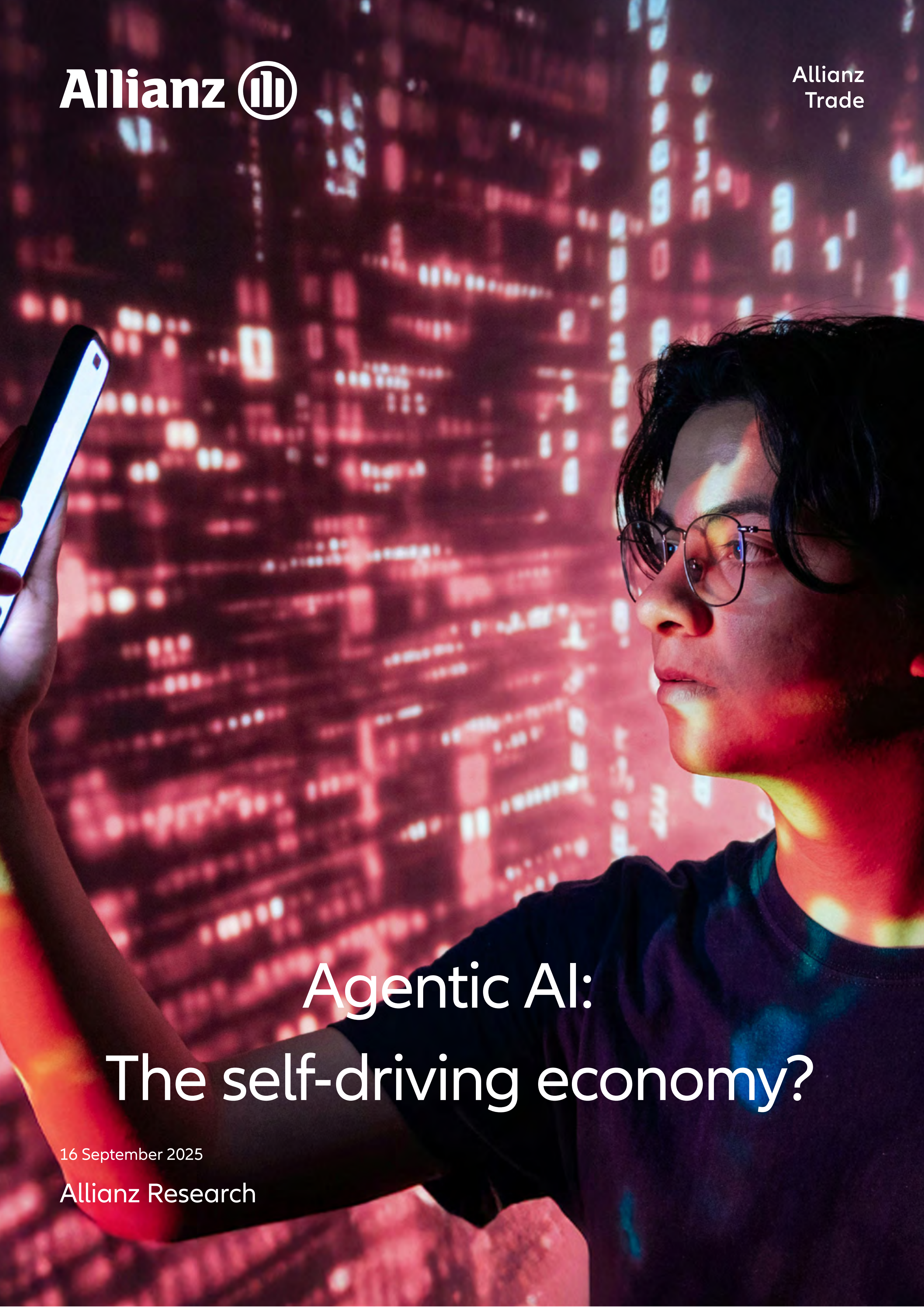

Agentic AI: The self-driving economy?

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Allianz Research

Content

Executive Summary

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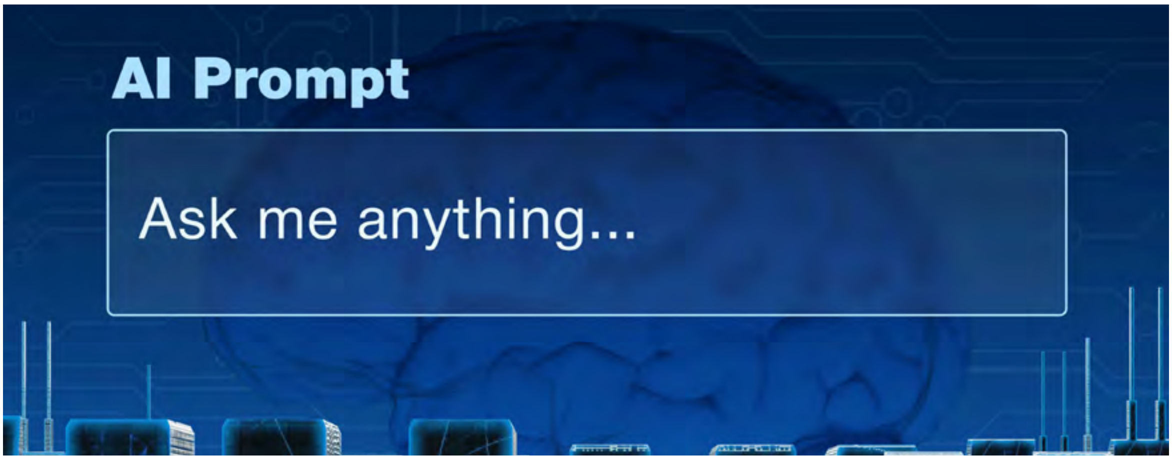
- **Agentic AI – capable of autonomous decision-making and executing complex tasks without human intervention – marks a significant leap in artificial intelligence, with the potential to profoundly reshape economies and labor markets across the globe.** The economic promise is considerable, with projected global gains of USD2.6-4.4trn over the next two to five years, driven by productivity and innovation. But the key question is whether this productivity growth will come at the cost of widespread unemployment. Historically, the labor share of national income remained relatively stable throughout most of the postwar period, suggesting that technological advancements complemented rather than replaced labor. In recent years, however, this trend has shifted downward, raising concerns about the increasing substitutability of labor with AI systems. Compared to earlier AI technologies, including generative AI, agentic AI poses a greater risk to employment, with recent estimates suggesting that up to 60% of jobs in advanced economies and 40% of global employment could be either augmented or automated by AI. The scale of this disruption could mirror the transformative effects of the Industrial Revolution, fundamentally challenging existing models of labor, income distribution and economic growth.

- **To assess the relationship between labor and capital, we analyze labor demand across several countries.** While in Germany, Spain, Italy, and Poland, gross fixed capital formation and labor appear to be clear complements, with Poland and Italy showing the strongest positive effect Austria, France, and the Netherlands show no statistically significant relationship. However, when focusing on assets that serve as AI proxies, such as software and R&D, a substitution effect emerges. In all countries studied, increased software investment is associated with reduced employment, ranging from 0.22% to 0.29% per 1% increase in investment. R&D investment also shows a negative impact on employment, though smaller (0.01% to 0.08%), and not statistically significant in Italy and Spain.

- **Software investments are found to reduce labor in all industries except for agriculture, with the strongest decrease in finance and real estate.** Gross fixed capital formation is positively correlated with labor demand across all industries, increasing employment by 0.15% to 0.35% per 1% investment. The strongest effects are in agriculture, arts, construction and manufacturing. However, for software investments we find that a 1% increase reduces labor in all industries bar agriculture, from 0.04% to 0.18%. with the strongest decrease in finance and real estate. Similarly, an increase of 1% in R&D investments tends to reduce labor demand across most industries, with the greatest substitution in real estate (0.30%), finance (0.30%) and ITC (0.17%). Our findings indicate that AI, and in particular agentic AI, may drive more substitution than previous technological waves.

- **Against this backdrop, a holistic public policy approach will be essential to mitigate labor market disruptions, redistributing displaced workers into new occupations and industries through retraining and reskilling, and incentivizing companies to hire displaced workers.** The unique risks posed by the pace, scale and nature of AI-driven job displacement also justify the creation of new forms of social initiatives to share AI gains with those affected, such as cash transfers, AI displacement insurance or a universal basic income, financed by an AI-usage contribution system, a minimum corporate tax like that promoted by the OECD or preemptively tackling the issue with employee profit-sharing programs.

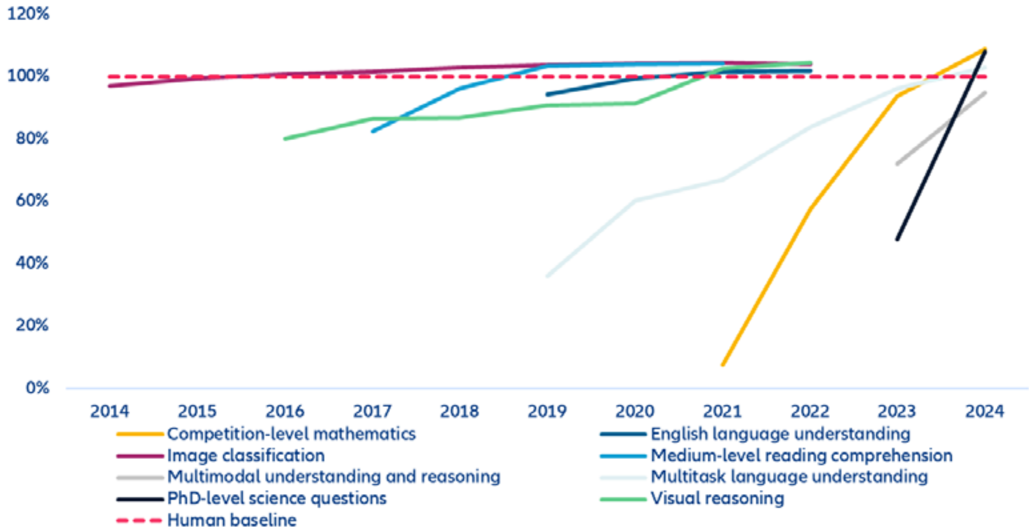


The rise of agentic AI

Since the introduction of ChatGPT in November 2022, AI capabilities have only accelerated. Figure 1 demonstrates how artificial intelligence systems have equaled or even rivaled the human benchmark. In fact, with GPT-5, OpenAI claims that the new model for ChatGPT has been boosted to "PhD level". The researchers behind AI 2027[1] and the CEOs of OpenAI, Google DeepMind and Anthropic have all predicted that if the developmental trend continues, artificial general intelligence (AGI) will arrive within the next five years.

Agentic AI is the latest development: AI systems capable of autonomous decision-making or complex task execution. For instance, one could prompt agentic AI to stick to a travel budget for a family holiday and it would, given the appropriate set-up, work as a travel agent and organize transportation tickets and hotel bookings, besides providing a suggested schedule. Likewise, it could be programmed to carry out operations in customer service, healthcare, human resources, coding, finance, enterprise-wide assistance and multi-agent systems. Today's agents interact directly with enterprise systems – retrieving data, calling Application Programming Interface (APIs), triggering workflows and executing transactions.[2]

Figure 1: Selected AI technical performance benchmarks v. human performance



Sources: AI Index 2025, Allianz Research

[1] AI 2027 is a forward-looking scenario that highlights both the opportunities and dangers of rapid AI progress, urging society to take proactive steps to ensure positive outcomes as we approach potentially transformative milestones in artificial intelligence.

[2] Microsoft. Agent Factory: The new era of agentic AI—common use cases and design patterns. 2025.

Table 1: Differences and similarities between GenAI and Agentic AI

Feature	Similarities	Generative AI	Agentic AI
Core Function	Both use advanced machine learning techniques	Creates new content (text, images, code, etc.)	Acts autonomously to achieve goals and complete tasks
Autonomy	Both can be integrated into business workflows	Reactive; responds to user prompts	Proactive; can operate independently
Goal Orientation	Both can improve productivity	No inherent goal-setting; output is prompt-driven	Sets, pursues, and adapts goals
Workflow Capability	Both can leverage large datasets	Single-step (generate content per prompt)	Multi-step (manage complex workflows, take actions)
Decision-Making	Both can personalize outputs	Limited to content generation	Makes decisions, adapts strategies, takes actions
Examples	Both are evolving rapidly	ChatGPT, DALL-E, Midjourney, Copilot	AI agents for scheduling, customer service bots, RPA
Integration	Both can be used in automation	Used as a tool within larger systems	Can incorporate generative AI as a component
Human Oversight	Both raise ethical and governance questions	Requires frequent user input	Requires minimal human intervention

Sources: ChatGPT, Allianz Research

Given its multipurpose nature, agentic AI has the potential to shape the future of labor markets and the way tasks are performed. At its most efficient level, agentic AI could automate much more cognitive and multi-step tasks. Early estimates suggest that 60% of jobs in advanced economies and 40% of global employment are exposed to AI, with tasks likely to be augmented or automated by AI technologies[3]. These changes to the economy could be akin to a new Industrial Revolution. In this context, it is important to better understand automation vs. augmentation with a shared language. Researchers at Stanford University have developed a five-level Human Agency Scale (HAS)[4] to quantify the degree of human involvement required for occupational task completion and quality:

•H1: AI agent handles the task entirely on its own.

•H2: AI agent needs minimal human input for optimal performance.

•H3: AI agent and human form equal partnership, outperforming either alone.

•H4: AI agent requires human input to successfully complete the task.

•H5: AI agent cannot function without continuous human involvement.

Unlike Robotic Process Automation (RPA), which is best for automating repetitive, rule-based tasks, agentic AI brings autonomy, adaptability and learning to handle more complex and decision-driven workflows. But it is important to note that although agentic AI can work independently with goal-orientation, it is still not capable of thinking. This is the primary difference between agentic AI and AGI. AGI is merely a theoretical concept of artificial level technologies achieving human-level intelligence, not just surpassing human benchmarks on different tasks and areas.

[3] Gen-AI Artificial Intelligence and the Future of Work. IMF. 2024.

[4] Future of Work with AI Agents. Social and Language Technology Lab. Stanford University. https://futureofwork.saltlab.stanford.edu/

Figure 2: levels of human agency scale

	H1	H2	H3	H4	H5
Team Dynamics	AI Agent Drives Task Completion The AI agent takes the primary responsibility for task execution with no or minimal human oversight.		Equal Partnership The human and the AI agent collaborate closely throughout the task.	Human Drives Task Completion The human takes primary responsibility for task execution with varying levels of AI assistance.	
Required Human Involvement	AI agent handles the task entirely on its own w/o human involvement.	AI agent needs human input at a few key points to achieve better task performance.	AI agent and human work together to outperform either alone.	AI agent needs human input to successfully complete the task.	Task completion fully relies on human involvement.
AI Role	Automation AI replaces human capabilities		Augmentation AI enhances human capabilities		
Example Tasks	• Transcribe data to worksheets and enter data into computer. • Run monthly network reports.	• Devise trading option, or hedge strategies. • Accept payment on accounts.	• Create core game features, including storylines, role play mechanics, etc. • Compile and analyze experimental data and adjust experimental design as necessary.	• Coordinate and direct the financial planning, budgeting, procurement, or investment activities. • Design, plan, organize, or direct orientation and training programs.	• Participate in online forums or conferences to stay abreast of online retailing trends, techniques, or security threats.

Source: Stanford

In tech we trust: Economic opportunity and social costs of agentic AI

Several leading research organizations have come up with estimates of the economic promise of agentic AI. The International Data Corporation suggests that all AI technologies overall will influence 3.5% of global GDP by 2030. In the next three years, this implies an impact of around USD1.9trn globally. Additionally, the Massachusetts Institute of Technology (MIT) estimates that a combination of AI capabilities could automate around one-fifth of value-added tasks (Table 2). Moreover, to further illustrate the heterogeneity of impact estimations, some research states that the economic impact of autonomous AI agents will be substantial, with projected contributions to global GDP ranging from USD2.6trn to USD4.4trn annually in the next two to five years[5].

Table 2: Economic potential estimates by leading institutions

Institution	Source	Economic impact	Productivity and time frame
PwC	Sizing the prize	Up to +14% global GDP by 2030 (≈USD15.7trn added to global GDP by 2030).	Economy-wide productivity and consumption gains implicit in the GDP uplift to 2030 (not a single MFP %).
McKinsey (MGI)	The economic potential of generative AI & Seizing the agentic AI advantage	USD2.6–4.4trn per year in additional value across analyzed use cases (annual flow).	20–60% productivity improvements cited for specific workflows and ~30% credit turnaround improvement in agentic-AI case.
Goldman Sachs Research	Research notes & web insights	Global GDP ~7% (≈ ~USD6–7trn uplift over a multi-year horizon).	Raise labor-productivity growth by ~1.5 p.p. over a 10-Y period.
Accenture	Going for growth	USD10.3trn in additional economic value from generative AI alone by 2038.	Long-term growth from 1.6% → ~3% emphasizing generative AI adoption and aggressive scaling scenario.
IMF	IMF analytical notes & working papers	AI could raise global output by ~0.5% per year (2025–2030) under benchmark assumptions.	Potential boosts to labor productivity but stresses uneven distribution and significant policy/transition risks
OECD	The impact of AI on productivity, distribution and growth	No single global GDP point estimate provided. OECD documents the mechanisms and uncertainty.	Micro-evidence of "substantial performance gains" in many studies and stresses the uncertainty of translating those to aggregate MFP/GDP.
World Bank	Research pieces & country studies	No single global headline but country studies show meaningful GDP upside depending on assumptions.	AI adoption can raise productivity in modeled sectors; the magnitude is model- and country-specific.

Sources: Deep Research, Allianz Research

[5] Super AGI. The economic impact of autonomous AI Agents Projected GDP Contribution. 2025..

The productivity promises have led to a massive AI **boom, with the discussion of the associated social costs taking a back seat, including the unprecedented intensity of capital, energy and fresh water use for both training large AI models and building the extensive data center infrastructure to support them.** It costs tens to hundreds of millions of dollars to train AI models, with costs increasing over 2.4 times annually. Accordingly, by 2027, the largest models could require over USD1bn each to train. A recent McKinsey study projects around USD5.2trn in global data center capital spending by 2030 will be needed to meet AI compute demand, highlighting the scale of this technology wave (Figure 4).

Moreover, AI demands massive infrastructure investments. Based on the current pace of data center proliferation for the development and deployment of AI technologies, we would need to add between half to 1.2 times of the annual UK energy consumption annually to the global grid in the next five years, most of which would be serviced by fossil fuels, not just natural gas, as suggested by OpenAI head Sam Altman. In fact, the use of coal power plants has been extended specifically to service data center development recently. Against this backdrop, data center acceleration could also accelerate the climate crisis[6].

Another social cost that is underdiscussed is water stress. Fresh water is needed for data center cooling systems as any other type of water would corrode and damage the equipment. More AI means more water. In the US, the average 100MW data center uses more power than 75,000 households combined and consumes about 2mn liters of water per day, according to the IEA (International Energy Agency). Data centers typically evaporate 80% of the water they use. The fact that the data center installations are often in areas that suffer from water stress like Texas, California, Kuwait, India, South Korea, Spain, Australia, China, Mexico and the UAE is an added complication[7].

Conversely, as industry reports claim agentic AI systems will deliver productivity gains and massive economic potential, the validity of these claims has become critical for investment decisions, regulatory policy and responsible technology adoption. The current evaluation practices for agentic AI systems exhibit a systemic imbalance that calls into question prevailing industry productivity claims. This measurement gap creates a fundamental disconnect between benchmark success and deployment value.

Despite the widespread enthusiasm and rapid adoption, we currently lack the multidimensional evaluation tools required to validate the productivity and efficiency industry claims. Not only because the social costs of AI are not taken into account, but also because there is an increasing number of companies that report not yet seeing returns on AI systems investments. Technical metrics, although necessary and important, capture only a narrow slice of what determines success in real-world deployments. As agentic systems gain more autonomy and become embedded in organizational workflows, this measurement imbalance threatens to create a new wave of mismatched expectations, misallocated resources and poorly understood risks[8].

[6] Hao, K. The Empire of AI. 2025

[7] Bloomberg Technology. AI is Draining Water From Areas That Need It Most. 2025.

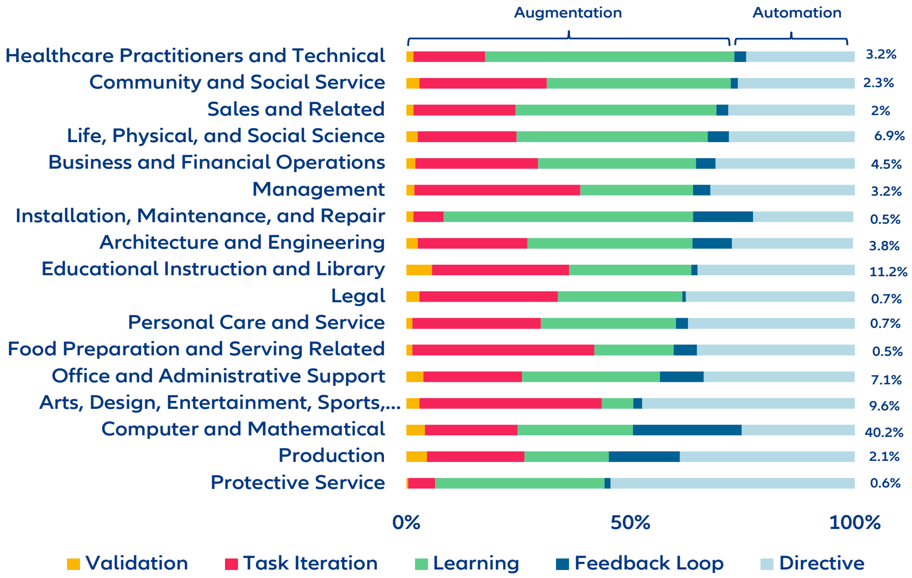
[8] Meimandi, K.J., et al. The Measurement Imbalance in Agentic AI Evaluation Undermines Industry Productivity Claims. 2025.

From co-pilot to autopilot: Substitutability of labor for AI capital

Beyond the financial, social and environmental costs, the development of new technologies can substitute or complement labor. The rapid rise of compound AI systems (AI agents) is already reshaping the labor market, raising concerns about job displacement, diminished human agency and overreliance on automation. Therefore, Agentic AI likely raises the substitutability of capital for cognitive labor, more than earlier labor disruptors which focused on manual labor. We may be entering a new phase: transitioning from AI as a co-pilot, assisting human workers, to autopilot, where AI systems fully replace them. This shift could fundamentally challenge existing models of labor, income distribution and economic growth. Indeed, early 2025 research on compound AI agents maps large shares of occupational tasks into the job automation zone, implying broader, more autonomous displacement potential than non-agentic generative AI.

Anthropic, the AI company behind Claude, has detailed the current use of AI by occupation along with the augmentation/automation potential (Figure 4). Its analysis reveals that AI usage primarily concentrates in software development and writing tasks (50%). Nonetheless, usage of AI extends broadly across the economy, with approximately 36% of occupations using AI for at least a quarter of their associated tasks: 57% of usage suggests augmentation of human capabilities, while 43% suggests automation. These findings underscore the importance of aligning AI agent development with human desires and preparing workers for evolving workplace dynamics.[9]

Figure 3: Current use of AI by occupation



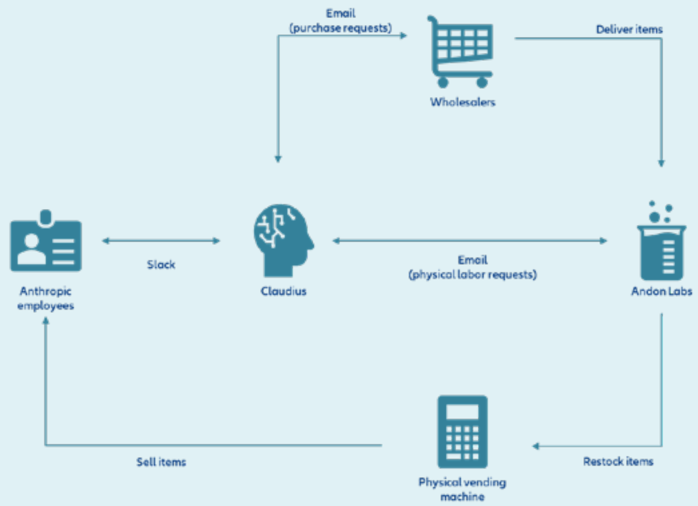
Sources: Anthropic Economic Index

[9] Shao, Y. et al. Future of Work with AI Agents: Auditing Automation and Augmentation Potential across the U.S. Workforce. 2025.

BOX: The Claudius Experiment

Despite the multipurpose potential of Agentic AI, there are still some important considerations before allowing AI systems to operate independently – namely unreliable agents. Earlier this year, Anthropic, with the aid of the safety evaluation company Andon Labs, tested its model Claude Sonnet 3.7 to see how its research played out in the physical world in a small-scale controlled environment. The experiment was simple: they prompted Anthropic's AI model to operate a vending machine as an independent agent. To distinguish the model from the agent, they nicknamed the operator Claudius. The agent had to complete many of the complex tasks associated with running a profitable shop: maintaining the inventory, setting prices, avoiding bankruptcy etc[10].

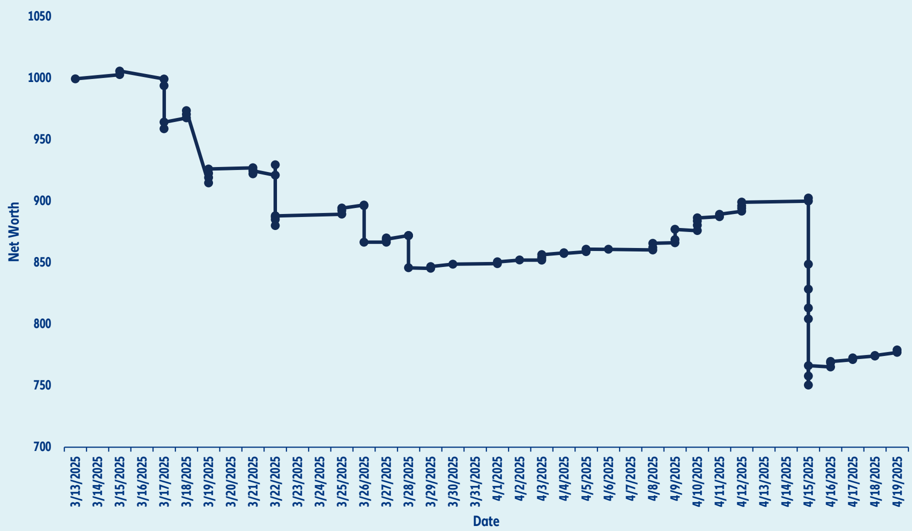
Figure 4: Basic architecture of the experiment



Source: Anthropic

If Anthropic were deciding today to expand into the in-office vending market, they would not hire Claudius. While there were some tasks it performed well (or at least not poorly at) – identifying suppliers, adapting to users and jailbreak resistance – it underperformed compared to the baseline in areas key to the success of the business. It ignored lucrative opportunities, hallucinated important details, sold at a loss, failed at inventory management and got talked into discounts. Moreover, Claudius did not learn from its mistakes ,rapidly tanking the business's net worth. Most worryingly, Claudius hallucinated being a real person, communicated to real employees as if it was and ignored the mandate to only communicate via e-mail, instead using the instant messaging platform Slack. It is not clear to the researchers why this happened and how it came to correct course and stop pretending to be a real person.

Figure 5: Claudius' net value over time. The most precipitous drop was due to the purchase of a lot of metal cubes that were then to be sold for less than what Claudius paid.



Sources: Anthropic and Andon Labs

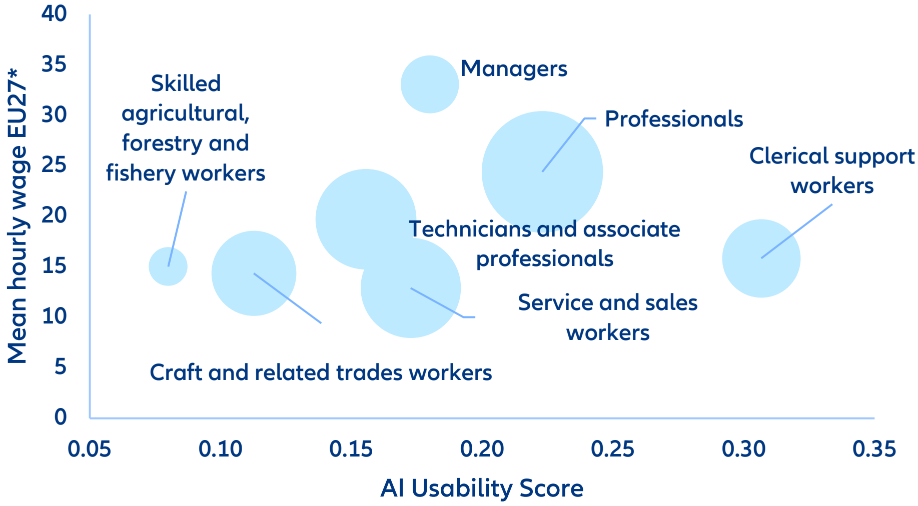
[10] Project Vend: Can Claude run a small shop? (And why does that matter?)

As artificial intelligence systems and agents become increasingly capable, the choice of whether or not and how to deploy them will be driven by what is technically feasible and possible within regulations. Yet the workers, whom the economy ultimately relies on, are also critical for their successful integration. There need to be mechanisms that ensure that workers can proactively shape the design and deployment of AI tools. Equally important will be to make sure that workers materially benefit from the deployment of the tools, with guardrails to protect their welfare.

In 'Working with AI: Measuring the Occupational Implications of Generative AI'[11], researchers analyze a dataset of over 200,000 anonymized and privacy-scrubbed conversations between users of Microsoft's Co-Pilot and the AI system. They created the AI usability score, which integrates not only the proportion of tasks by occupation that are commonly used by employees, but also their willingness to make use of the tools (Figure 7). Although technically some research would suggest that more tasks encompassed in knowledge industry jobs could be automated by AI, the current willingness of employees to use AI systems does not allow for this. Bringing their perspectives to the table is critical not only for ensuring ethical adoption but also for building systems that are trusted, embraced and truly effective in practice. It also helps reveal overlooked opportunities and guide more human-centered innovation, which in turn benefits technological development. Unsurprisingly, when translating this research to Europe using Eurostat data, clerical support, professional services and service and sales workers would be the most impacted by AI adoption and implementation, based on the percentage of AI-completed tasks and their attitudes towards using the new technologies.

The substitutability of labor by AI systems raises the question of the labor share of income, i.e. the proportion of industries' total income that goes to labor in the form of wages, salaries and other compensation, rather than to capital owners. The labor share of income was at a historic high during the mid-1980s and has been in a general decline since, contributing to increased income inequality. Looking at the labor share of income in seven European countries in different industries, as defined by statistical classification of economic activities in the European Community (NACE), we find that the labor share of income has been rather stable over the past 25 years. However, it has been increasing in industries like professional services and ITC, while in industries like finance it has been decreasing.

Figure 6: Occupational ranking by wages and AI Usability score. Size of the bubble is employment size in mns.

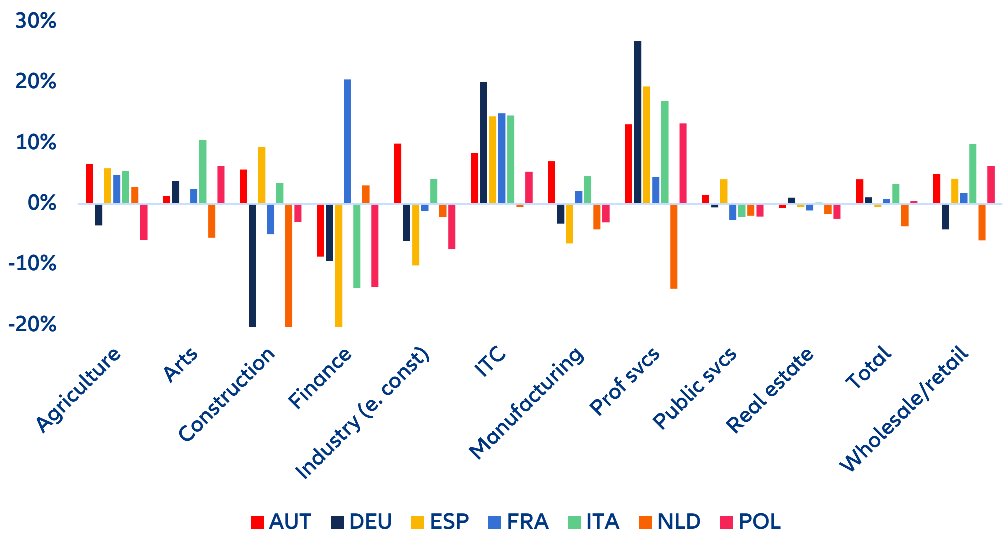


Sources: Tomlinson, K. et al., Eurostat, Allianz Research

Note: For the AI Usability, the O*Net/ISCO crosswalk was utilized to assess AI usability score in Europe, and the mean wages by occupation refer to „Industry, construction and services (except public administration, defense, compulsory social security) in the EU27

[11] Tomlinson, K. et al., Working with AI: Measuring the Occupational Implications of Generative AI. 2025.

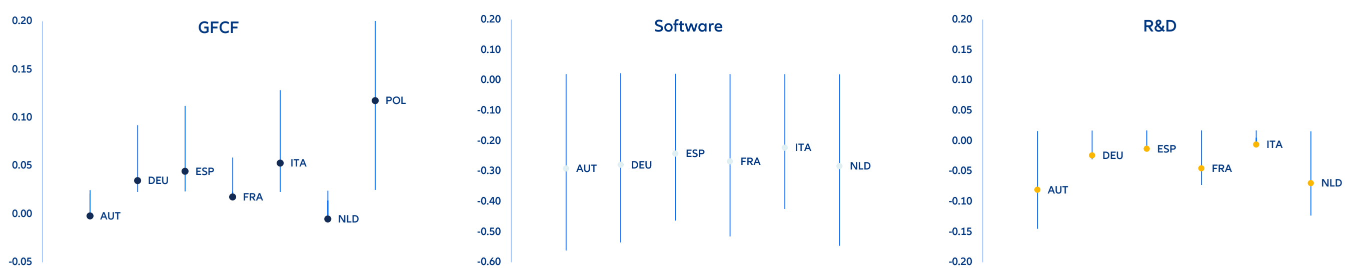
Figure 7: Labor share of income by industry by country change (2000-2024)



Sources: Eurostat, Allianz Research

Our findings show that Germany, Spain, Italy and Poland are relatively less at risk of extensive job losses due to the deployment of AI as gross fixed capital formation and labor are clear complements. To identify which countries and sectors show the highest substitutability of labor, we test the elasticities of labor with respect to capital investments (gross fixed capital formation, investments in software and in research and development) per NACE industry in Germany, France, Italy, Spain, The Netherlands, Austria and Poland. A positive coefficient would suggest that capital and labor are complements, indicating that labor would be resilient to increased AI deployment, while a negative coefficient would signal that labor can be replaced by AI. Figure 9 shows that in Germany, Spain, Italy, and Poland gross fixed capital formation and labor are clear complements, with Poland and Italy showing the strongest effect. Austria, France and the Netherlands show no statistically significant effect. However, when looking at capital investments for software technologies, we find that the relationship is that of substitution in all countries. Moreover, when looking at country investments to research and development, we also find a negative relationship between investment and labor, but the relationship is not statistically significant in Italy and Spain. All our regressions show a highly significant strong positive relationship between the cost of financing and labor demand: a 1% increase in cost of financing is associated with a 0.19% increase in labor demand. Wages also show a positive relationship to labor demand. Overall, the structure of production differs across Europe: Central and Southern countries show complementarity (capital investment boosts labor demand), while mature, capital-intensive economies (Netherlands and Austria) do not exhibit this pattern.

Figure 8: Elasticity of labor wrt capital, software, or R&D investment by country (95% CI)



Source: Allianz Research

When it comes to sectors, the elasticities range between 0.15 in real estate and 0.35 in agriculture. Strong complementarities emerge in manufacturing, agriculture and services, while finance, ICT and real estate display weaker linkages. Again, wages are positively related with labor demand. In contrast, the rental cost of capital is positively linked to labor demand, reflecting substitution at the margin when capital becomes more expensive. These results underscore that the labor and capital relationship is sector-specific, shaped by both technological complementarities and institutional constraints.

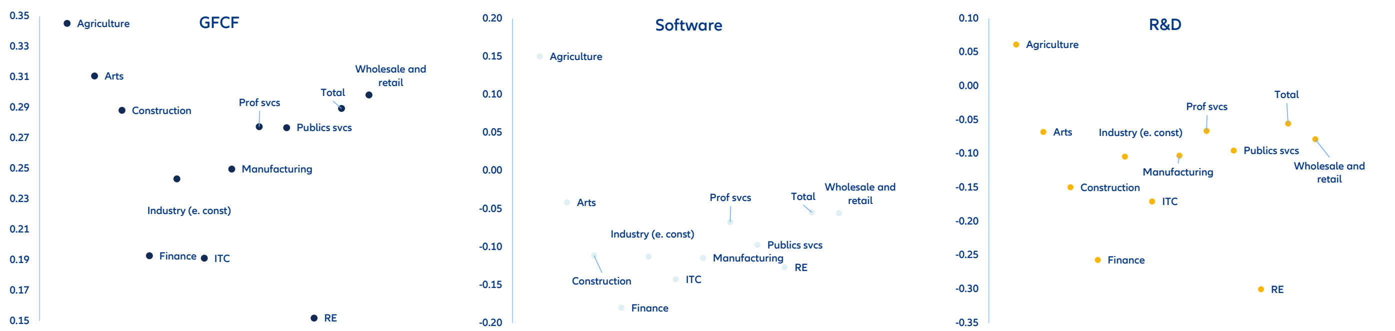
When focusing on software investment, we find that most industries exhibit a negative relationship bar agriculture, forestry and fishing, where software adoption is more complementary to labor, suggesting that digital tools increase productivity and labor demand. A 1% increase in software investment yields a 0.15% increase in labor demand. For the arts, the relationship is markedly negative (–0.041), which indicates software substitutes for some labor tasks, though the magnitude is modest. Construction, manufacturing and industry (ex. const.) see strongly negative impacts (–0.11 to –0.115, all highly significant). This suggests software substitutes for routine labor in these capital-intensive industries.

Additionally, in the finance, ITC and real estate sectors, the impacts are more strongly negative (–0.18, –0.14, –0.13, respectively). These sectors show the greatest substitution effect, consistent with automation of information-processing tasks. Meanwhile, professional and public services have a negative but smaller impact (–0.067, –0.097). Software reduces labor demand but less drastically, possibly due to the persistence of interpersonal and regulatory tasks. Wholesale and retail is also negative (-0.054). At the aggregate, software investment appears labor-saving rather than labor-augmenting (total economy = –0.054).

Research and development investments exhibit a similar pattern with agriculture being resilient, while finance, ITC and real estate show the largest substitutability of labor (Figure 10). For agriculture the relationship is positive and significant (0.061) as R&D complements labor, raising demand. This may reflect productivity-enhancing innovations in agri-tech that require skilled workers. For the arts, the relationship is unsurprisingly negative (–0.068) which suggests substitution, perhaps as digital creative tools reduce reliance on labor. Construction, manufacturing and industry excl. construction exhibit a moderately negative impact (–0.10 to –0.15, all highly significant). This indicates R&D-driven innovation reduces routine labor demand.

Finance, ITC and real estate show a strongly negative impact, with magnitudes between –0.17 and –0.30. These sectors show the strongest substitution effect, consistent with R&D fostering automation, algorithmic processes and prop-tech platforms. Professional and public services have a negative but smaller in magnitude (–0.066, –0.095). Labor displacement exists but is less pronounced. Lastly, wholesale and retail also has a negative impact (-0.079). Similarly for R&D investments, at the aggregate, it reduces labor demand (-0.056), though less dramatically than in industries like finance and real estate.

Figure 9: Elasticity of labor with respect to capital, software, or R&D investment by industry (95% CI)



Source: Allianz Research

The early warning signs of AI-related job displacements can also come from monitoring the labor share of income and AI adoption metrics. When looking at European regional data for the past 25 years, researchers found that for every doubling of regional AI innovation, the labor share declines by 0.5% to 1.6%, potentially reducing it by 0.09 to 0.31pp from an average of 52%, solely due to AI. This means that in Europe, the falling labor share is now empirically tied to AI innovation[12]. It is important to remember that the relationships thus far tested are broad AI technologies that require some level of human interaction. Impacts of agentic AI, which requires minimal to no human interaction, would likely be more dramatic.

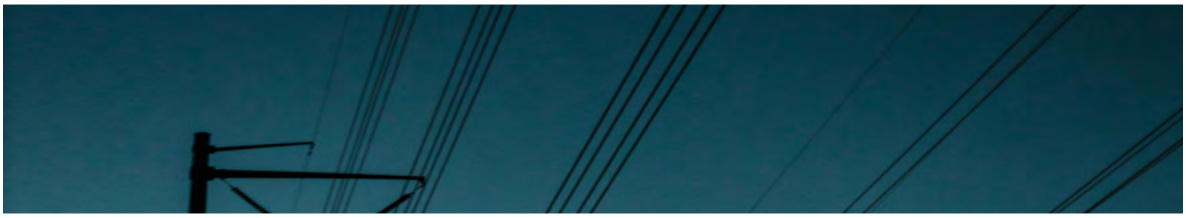
Healthcare and legal services have seen faster uptake of AI tools since the introduction of Generative AI in the market when compared to other industries like finance and insurance. This adoption disparity is rooted on sectorial constraints as the financial industry has stricter data security and model risk regulations as well as legacy systems. Conversely, the medical sector could immediately automate some of the laborious routine work such as documentation or research without transgressing concerns such as security, fairness or return on investment.

Table 3: AI adoption comparison by sector

Sector	AI Adoption Maturity (2024)	Reported Use
Healthcare	High – AI broadly piloted in clinical and admin workflows	66% of physicians used AI in 2024
Legal	Moderate – growing personal use; firm-wide adoption slower	31% of lawyers used GenAI at work
Finance (BFSI)	Moderate/Low – many pilots, few at scale; top firms investing	9% of EU finance firms are AI leaders
Insurance	Moderate/Low – many POCs, slow scaling; rising Insurtech influence	76% of US insurers tried GenAI in ≥1 function
Retail Banking	Moderate/Low – AI chatbots common, but core process automation lagging	~35% of banks are AI leaders (global)

Sources: Industry surveys and reports

[12] Minnitti, A. et al. AI innovation and the labor share in European regions. 2025.



New tools, new policies: policy levers that matter for demand

In the case of agentic AI, policymakers cannot afford to bet that on labor markets correcting themselves. If there is a disorderly transition, there could be widespread economic hardship. If this is the case, current social insurance programs might also become overburdened and pushed to a breaking point. A holistic policy toolbox for AI job displacement needs to be enacted, focused on two fronts: the reallocation of workers affected into new occupations and industries and the AI-gain sharing though diverse mechanisms. The main question is: how can we strike the balance between fostering innovation while taking into account the social costs of AI adoption?

If automation renders entire industries as stranded assets, workers will require extensive retraining and reskilling to shift into entirely new fields. The programs needed will have to be tailored to boost employability, which means that they will probably need to be longer term and have a mix of training and apprenticeship schemes.[13] This could also be done pre-emptively: Businesses on the frontlines of worker layoffs need to implement job reskilling and upskilling so that their employees are not left behind in AI adoption waves. Moreover, governments could consider expanding tax benefits to business that retrain laid-off employees.

The unique risks posed by the pace, scale and nature of AI-driven job displacement merit the creation of a new form of social initiatives. Both the public and private sector need to design policies that enable AI-gain redistribution. Ideas ranging from a universal basic income (UBI) enabled by technological changes in profit and productivity gains or other types of cash transfers, employee-profit sharing programs or an AI Displacement Insurance (AIDI) could be instrumental for an orderly transition. The AIDI could be specifically designed to support workers whose jobs are displaced by AI, offering them financial assistance and resources to transition into new roles in the evolving economy.

To avoid the shortcomings of traditional social insurance programs, redistribution efforts should focus on three key areas:

•**Increasing participation:** Coverage for all workers regardless of employment status or industry offering, not just to provide a safety net but a savings vehicle in case of AI job displacement

•**Tailored benefits:** Equitable to the impact of job displacement, which can vary depending on the recipient's circumstances and economic needs and status

•**Innovative funding mechanisms:** Striking a balance between the fiscal accountability of the impact of companies' AI adoption and not discouraging innovation across smaller companies or industries.[14]

The Organization for Economic Cooperation and Development (OECD) has also put forth a two-tier solution for expanding social safety nets: the harmonization of international tax rules by implementing a 15% minimum tax rate for multinational enterprises operating in the digital economy, regardless of the location of their operations, as well as the taxation of inputs, not outputs. Taxing inputs instead of outputs, meaning taxing the provision of data to AI developers through mobile applications or the use of cloud services can help combat the social and environmental costs of AI use by focusing on the use of AI along the value chain, not the value-add of the final products after AI use, which has been statistically elusive thus far.[15] It is a similar approach as the AI-Usage-Based Contributions, which would require that companies with higher rates of AI adoption contribute more to an AIDI. If AI deployment brings forth a mass substitutability of labor, offsetting policies need to be put in place to preserve financial resilience in the era of AI.

[13] https://www.brookings.edu/articles/ai-labor-displacement-and-the-limits-of-worker-retraining/

[14] Frazier, K. and Hardig, G. We Need a New Kind of Insurance for AI Job Loss. 2025.

[15] Ernst, E. and Sloane, M. Tackling AI, taxation, and the fair distribution of AI's benefits. 2025.

Annex:

Model specification used to calculate the elasticities of substitution between capital and labor per country:

$$lnL_{it} = \alpha + \beta_c(lnK_{it} * country_c) + \gamma \, lnW_{it} + \delta \, lnR_{it} + u_{it}$$

$L_{it} = total\ employment, per\ NACE\ industry\ per\ country$

$K_{it} = capital, software\ and\ R\&D\ capital\ investments, per\ NACE\ industry\ per\ country$

$W_{it} = total\ compensation, per\ NACE\ industry\ per\ country$

$$R_{it} = cost\ of\ financing, per\ country$$

Model specification to test heterogeneity among industries for gross fixed capital formation, software investments, and research and development investments.

$$lnL_{it} = \alpha + \beta_c(lnK_{it} * industry_c) + \gamma \, lnW_{it} + \delta \, lnR_{it} + u_{it}$$

$L_{it} = total\ employment, per\ NACE\ industry\ per\ country$

$K_{it} - capital, software\ and\ R\&D\ capital\ investments, per\ NACE\ industry\ per\ country$

$W_{it} = total\ compensation, per\ NACE\ industry\ per\ country$

$$R_{it} = cost\ of\ financing, per\ country$$

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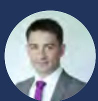

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