The uneven future of work: GenAI and labor market

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Content

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This article offers insights into the medium-term impact of generative AI (GenAI) on labor markets in the USA, Europe, the Middle East, and Africa. The aim is to quantify the proportion of tasks which AI could absorb over the next decade, while considering the economic feasibility of such shifts.

In brief:

- GenAI's influence on jobs is uneven, with highly skilled occupations facing more significant artificial intelligence (AI) exposure and potential job transformation.
- The economic benefits of AI, largely driven by wage disparities, play a crucial role in determining the feasibility and extent of GenAI adoption in different regions.
- Consequently, the potential for automating or augmenting tasks over the forthcoming decade varies significantly between regions. It is almost 10 times higher in Western Europe and the USA than in Sub-Saharan Africa.

We expand upon the earlier EY article on the impact of GenAI on the labor market, which focused on the USA, and extend this analysis in two directions. First, our study broadens the geographical scope to encompass five regions: Western Europe, Southern Europe, Central and Eastern Europe, the Middle East and North Africa, and Sub-Saharan Africa[1]. Second, we account for economic returns from implementing GenAI, drawing upon Daron Acemoglu's recent projections for AI implementation in the USA. This allows us to offer a more nuanced outlook on the relative regional impact of GenAI in the decade to come.

1 Western Europe includes Germany, France, the UK, Switzerland, Austria, Benelux, and Nordic countries. Southern Europe covers Portugal, Spain, Italy, and Greece. Central and Eastern Europe includes the Baltic countries, Poland, Czechia, Slovakia, Hungary, Ukraine, Moldova, Romania, Bulgaria, Albania, and the countries of the former Yugoslavia. The Middle East and North Africa covers Gulf Cooperation Council countries (except Saudi Arabia due to lack of data), Iraq, Syria, Lebanon, Egypt, Tunisia, Algeria, and Morocco. Sub-Saharan Africa includes the remaining African countries.

Key findings:

- **AI exposure differs between occupations:** Unlike earlier digital innovations, such as robotics, advanced manufacturing, and software, the impact of GenAI is largely concentrated on highly skilled roles, including professionals and technicians. Plant operators and skilled agricultural workers also face significant exposure to AI. Conversely, manual jobs and those requiring human interaction – such as service and sales workers, or clerical support – face low exposure to AI.
- **Agriculture skews the apparently uniform AI exposure between regions:** At the regional level, a higher concentration of an occupation that is highly susceptible to AI often offsets a lower incidence of another similarly exposed occupation. As a result, the average exposure to AI technologies seems to be uniform across regions. However, the range of farm sizes in the agricultural sector, and thus the nature of agricultural tasks, necessitates adjusting AI scores, leading to reduced exposure in some regions, especially in Sub-Saharan Africa.
- **Wage disparities significantly impact the economic gains from AI implementation:** Similar exposure to AI does not ensure equal implementation potential of regions. In countries with lower wages, the economic benefits of replacing or supplementing labor with GenAI are proportionally smaller. Wages in most of the analyzed regions, apart from Western Europe, are notably lower than those in the USA, the potential for AI deployment in these areas is correspondingly reduced.
- **The potential for AI-driven task automation or augmentation varies significantly between regions:** By combining the exposure of occupations to AI with labor market structure and wage levels, we discover that over the next 10 years, approximately 5% of tasks can be profitably automated in the USA and Western Europe, 4% in Southern Europe, 3% in the MENA region, 2% in Central and Eastern Europe, and 0.5% in Sub-Saharan Africa. Additionally, tasks that may not be automated over the next decade will still experience a growing impact from AI, as discussed in previous article written by EY teams.

Chapter 1

Decoding GenAI: analyzing AI exposure by occupation

AI exposure differs between occupations; it is more prevalent in jobs which involve detection of patterns, making judgments, and optimization.

GenAI does not need to displace jobs

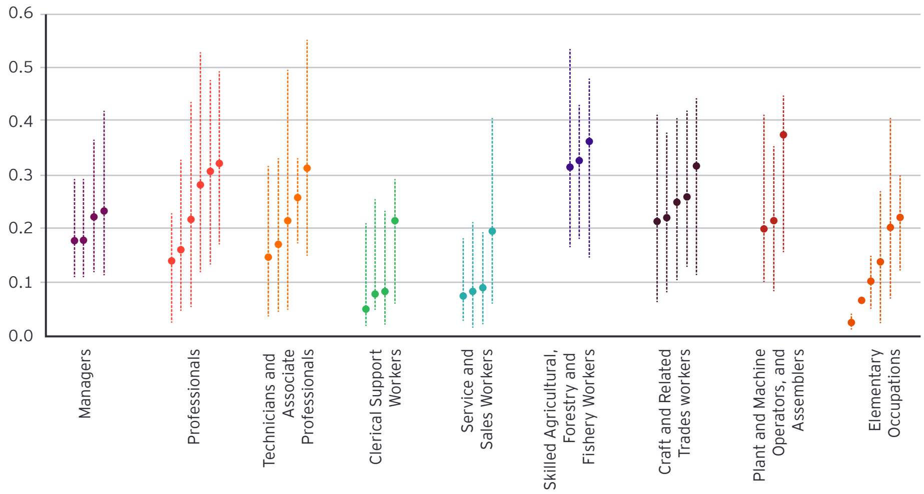
GenAI capabilities are already impressive, and as the technology progresses, an increasing array of tasks will involve delegation to AI systems. However, implementing AI in the workplace does not necessarily lead to job losses. Research indicates that GenAI's influence on labor demand and wages is not straightforward, since several processes occur concurrently:

- **Job displacement** may occur as AI models take over and reduce costs for certain tasks. For instance, various data-intensive functions, such as data classification, advanced pattern recognition, and computer vision tasks, are among those that can be profitably automated.
- **Job transformation** can take place due to the complementarity of workers and AI, which may automate some tasks and enable workers to specialize further, thus raising their productivity in other aspects of their job.
- **Job creation** may result from AI's potential to unleash human creativity, prompting the development of new tasks, occupations, and products. Moreover, as AI-driven productivity grows, it can spur the overall economy and increase the demand for labor.

How we calculate exposure to AI by occupation

To determine the impact of GenAI on the labor market in general and the scope of GenAI-driven task automation or augmentation in particular, we need to understand how different occupations will be affected over the next decade. Following previous article on GenAI and the labor market written by EY teams, we sourced insights from Michael Webb's paper, which assesses the exposure to AI of occupations in the USA. Webb uses the overlap between the descriptions of job tasks and AI patents to construct a measure of the exposure of tasks to AI automation. Then he adjusts the importance and frequency of tasks within an occupation to obtain a weighted occupational AI exposure score.

Figure 1: AI exposure across 40 international occupational sub-major groups applied in our study. We group scores by major occupational groups. Lines correspond to the 10%–90% percentage range of AI exposure scores among corresponding O*NET occupations.



Note: Occupations with higher AI scores have higher AI exposure. As note by Michael Webb there is no straightforward way to interpret his original scores in absolute terms, one should concentrate on relative terms. Thus, we normalize the original scores into a 0 to 1 scale.

Source: Webb (2020), EY Parthenon, BLS, EY EAT

Webb's study employs the US-specific O*NET occupational classification system, which varies from the systems used in Europe, the Middle East, and Africa. To derive AI exposure scores that we may apply in the subsequent stages of our analysis, we map his results onto the International Standard Classification of Occupations (ISCO) at the level of 43 distinct occupational groups.[2]

GenAI differs from previous technological advancements

Looking at the AI exposure scores across analyzed occupations, the key finding is that GenAI differs from earlier digital innovations such as robotics, advanced manufacturing, and software. While robots handle physical tasks and software manages routine data processing, AI performs tasks that involve detecting patterns, making judgments, and optimization.

For this reason, professional and technical occupations stand on the frontline of AI exposure. These roles often involve research, reporting, and data analysis – tasks that AI can significantly enhance. For instance, the integration of AI into drug discovery has notably sped up advancements in the pharmaceutical sector.

Assemblers whose job requires, among other things, reviewing work orders, specifications, diagrams, and drawings to determine the materials needed and assembly instructions, also have a high AI exposure score (0.37).

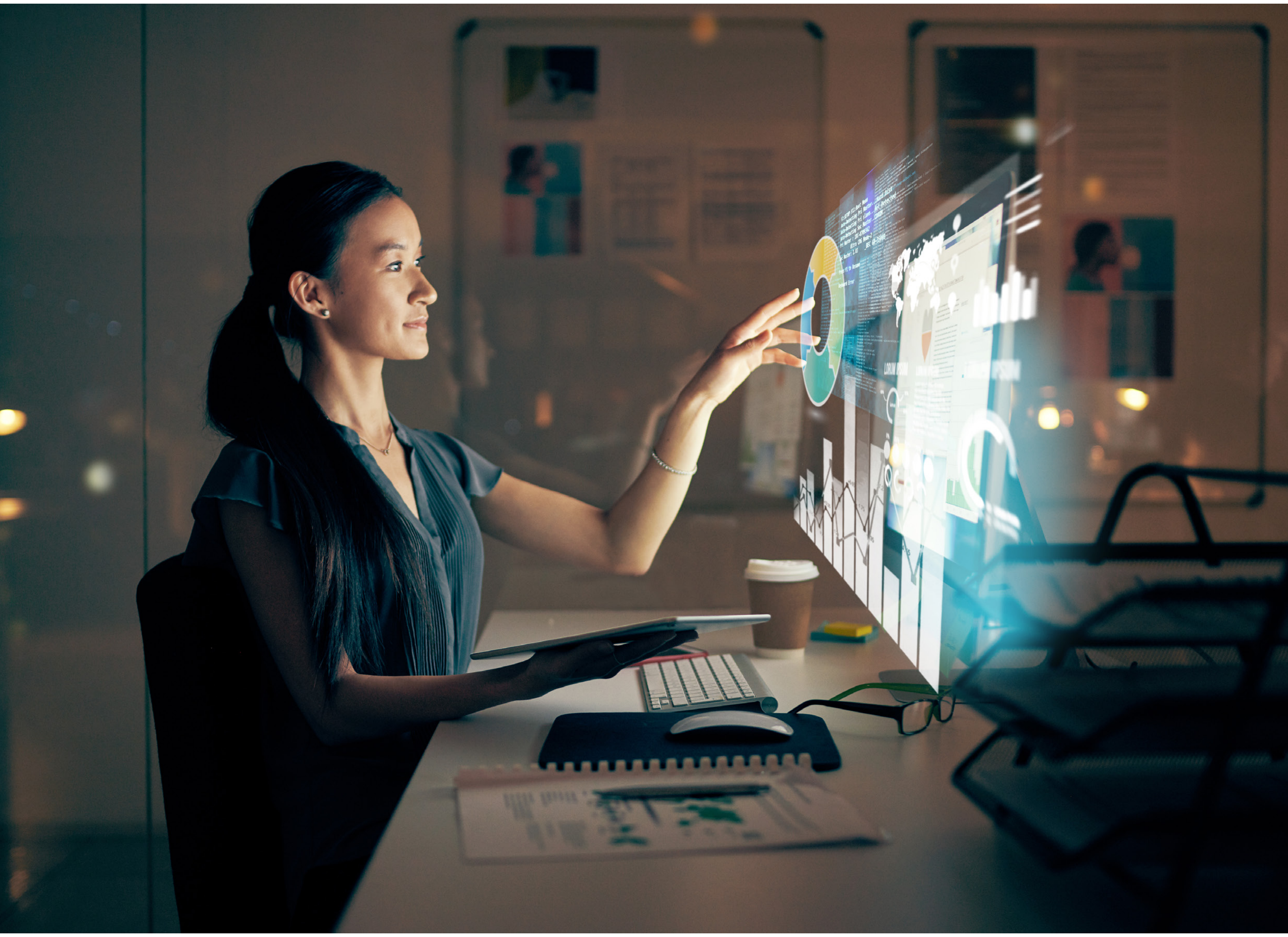
2 For our analysis, we focus on 40 occupational groups, excluding three related to military activities. While the ILO labor market database is rich, it implies limitations. Ukraine and South Africa use ISCO – 88 coding instead of ISCO – 08 coding resulting in 27 instead of 40 sub-major occupation groups. Furthermore, for 7 out of 15 countries in MENA and 10 out of 48 countries in Sub-Saharan Africa data for only nine major occupational groups were available. For those 19 exceptions, we aggregate AI exposure scores accordingly.

Furthermore, skilled workers in agriculture, forestry and fishery are also considerably exposed to AI (score between 0.31–0.36) stemming from their data-intensive work such as geospatial analysis for pest control and soil quality assessment, which AI can refine.

In contrast, occupations that require a high degree of human interaction, such as personal care workers (AI exposure score of 0.08) and teaching professionals (0.14), are much less vulnerable to AI influence.

Moreover, lower-skilled jobs, historically subject to automation by robotics and software, now show lower AI exposure. For example, food preparation assistants face minimal AI impact (0.03), despite high robotization. Numerical and material recording clerks also have low AI exposure (0.08) but are greatly impacted by software automation.

Finally, GenAI exposure is highly occupation-specific with significant variations even within the same occupational group. For example, within the legal, social and cultural professionals group we can find dancers and poets with some of the lowest scores and political scientists, who are among occupations most influenced by AI developments.



Chapter 2

Navigating the labor market landscape: factors influencing AI implementation between regions

Differences in regional labor market composition balance each other, resulting in similar average AI exposure. However, wages are a key differentiator in the potential for AI implementation.

Although our analysis assumes that occupational AI exposure scores do not differ between regions, apart from agriculture,[3] this does not imply uniform AI implementation possibilities. The defining factors analyzed in this article include: (1) the composition of each region's labor market and crucially, (2) wage levels within those markets.

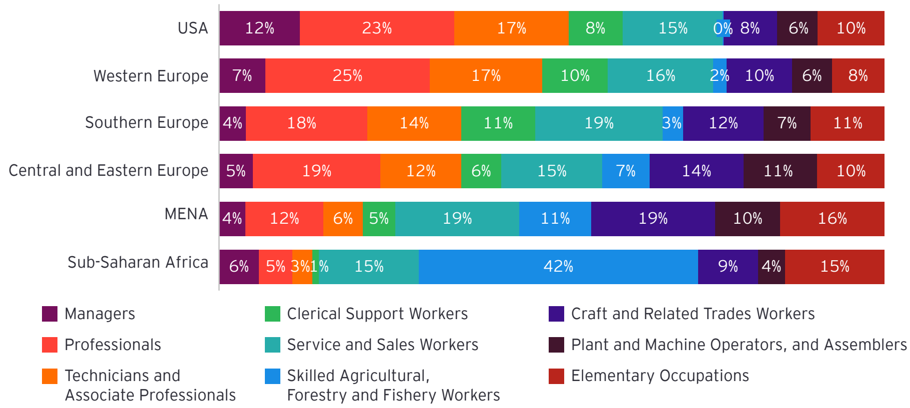
Labor market composition varies greatly between regions

Labor market composition varies significantly across analyzed regions — see Figures 2 and 3, which describe labor market in terms of employment and wage bill shares across major occupational groups, respectively.

In the USA and Western Europe, professional and technical, highly skilled white-collar jobs with high AI exposure, constitute a large part of the labor market. In the USA, these groups represent 40% of total employment, accounting for nearly half (48%) of the wage bill. Western Europe sees even higher figures, with 42% of employment and 50% of wages allocated to these jobs.

3 Below, we discuss an additional "agricultural-adjustment" in which we adjust the AI exposure for agriculture-related occupations to zero in Sub-Saharan Africa, MENA, Central and Eastern Europe, and Southern Europe.

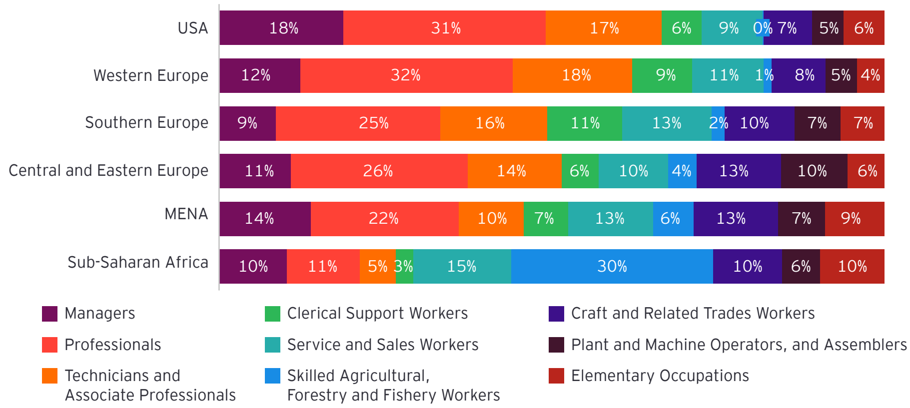
Figure 2: Labor market composition in analyzed regions, according to share of employment



Note: Employment-based shares are proportional to the number of workers within each occupation in each region based on ILO data. Please note that our calculations are based on 40 sub-major groups; however, the graph displays the results according to major occupational groups for clarity.

Source: ILO, EY EAT.

Figure 3: Labor market composition in analyzed regions, according to share of the wage bill



Note: Wage-bill-based share corresponds to the share of wages collected by workers in given occupation and region based on ILO data.

Source: ILO, EY EAT.

The Southern European labor market is characterized by a relatively high proportion of job categories with less AI exposure, such as service and sales workers or clerical support workers. In Central and Eastern Europe, the labor market has the most diverse structure of all regions with relatively low differences across occupation group shares.

The MENA region has a relatively high proportion of craft and related trade workers who are relatively prone to AI. Additionally, while professional, technical and managerial jobs account for a relatively smaller share of employment, they command a wage share comparable to one observed in Southern Europe or in Central and Eastern Europe.

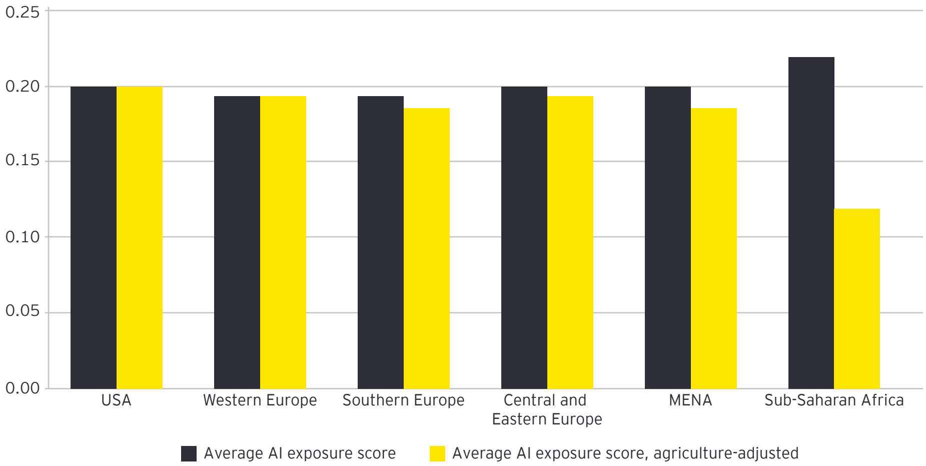
A unique feature of the Sub-Saharan African labor market is the prominent number of agriculture, forestry and fishery jobs. Yet high AI exposure in these occupations does not necessarily equate to substantial AI implementation, predominantly due to lower wages and relatively small farm sizes in this region, as detailed below.

Agriculture and the paradox of GenAI exposure

The influence of GenAI varies greatly between occupations, as highlighted in our previous discussion. A closer look at the labor market suggests that those differences balance out and AI exposure seems to be consistent across regions. However, the agricultural sector, with its diverse farm sizes, and thus task characteristics, justifies modifying AI scores. This adjustment reduces exposure levels in some regions, especially in Sub-Saharan Africa.

To calculate the average AI score for each region, as shown in Figure 4, we assign weights to the AI scores of individual occupations (see Figure 1) based on their share of the regional wage bill (Figure 3). However, agricultural occupations present unique challenges due to their diversity across regions. To tackle this issue, we present an alternative set of results, in which we adjust the AI exposure for agriculture-related occupations to zero in Sub-Saharan Africa, MENA, Central and Eastern Europe, and Southern Europe.

Figure 4: AI exposure across regions: wage bill average weighted score with and without adjustment for employment in agriculture



Note: To calculate the average AI score for each region, we weigh the occupational AI scores by share of a given occupation in the regional wage bill ("Average AI exposure score"). For regions which are characterized by a relatively low average farm size, and thus less data-driven tasks associated with agriculture, we adjust the AI exposure score to zero ("Average AI exposure score, agriculture-adjusted"). Average regional AI scores are used purely for illustrative purposes. In our final analysis, we use disaggregated results at a country-occupation level.

Source: ILO, EY EAT.

This adjustment reflects the varied farm sizes between regions,[4] influencing the degree to which data analytics – and consequently AI automation – can be integrated into agricultural practices. For example, the average farm size in Sub-Saharan Africa is 9 hectares while it amounts to c.a. 180 hectares in the USA. Regions such as MENA, Central and Eastern Europe, and Southern Europe also have relatively smaller farms compared to the USA or Western Europe, however, the differences are less prominent.

If we abstract from the regional characteristics of agriculture-related occupations, we find an unexpected pattern: the highest AI exposure score, exceeding 0.22 is found in the Sub-Saharan African region. This is closely tied

4 For further insights, one can refer to statistics from Our World in Data, Eurostat, the research by Leah Samberg and her co-authors or paper by Olaf Erenstein and his coauthors.

to the substantial agricultural workforce within this area. However, when we consider agriculture-adjusted AI exposure, the scores fall to 0.12. For other regions, the average AI score ranges between 0.18 and 0.20, with a much more limited impact of the agricultural adjustment.

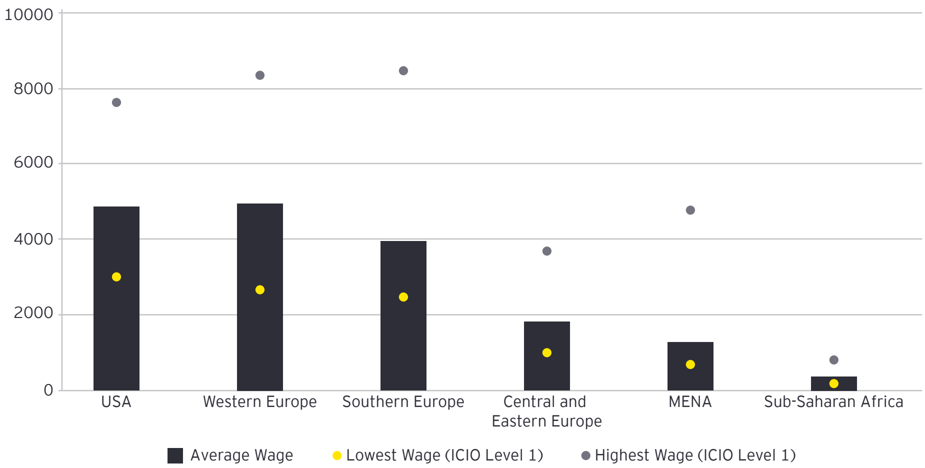
It is important to note that our estimates present two distinct scenarios, while the true AI exposure likely falls somewhere between the unadjusted and agriculture-adjusted metrics.

GenAI adoption potential: weighing economic gains against global wage differentials

GenAI exposure significantly impacts its adoption, but the other side of the coin is the economics of such an investment. While AI can boost productivity by automating or augmenting certain tasks, the tangible benefits for companies hinge on employee wages. In essence, an alternative to AI adoption could be to retain these tasks within human hands.

Wages vary widely between regions, as illustrated in Figure 5. The graph also highlights the span between the lowest and highest wages within major occupational groups in the analyzed regions.

Figure 5: Average monthly wages and lowest and highest monthly wages within major occupational groups from the analyzed regions.



Note: Values in the graph illustrate the average monthly wage measured in 2017 purchasing power parity dollars ($PPP). In the case of the "Lowest" and "Highest" wages we aggregate wages at country-occupational levels to the region-occupational level based on the country wage bill share.

Source: ILO, EY EAT.

On average, wages are the highest in the USA and Western Europe, with Western Europe even slightly outpacing the US after adjusting for purchasing power.

The remainder of the analyzed regions show significantly lower average wages. For example, average wages in Southern Europe are about 80% of those in the USA, while the respective ratio for the Central and Eastern Europe amounts to only 40%. These figures fall even further to 26% in the MENA region, and merely 7% in Sub-Saharan Africa.

The disparity in wages within regions is also notable. The MENA region has the broadest wage distribution, largely due to exceptionally high salaries for managerial and professional roles in Qatar and the United Arab Emirates. On the other end of the spectrum, Sub-Saharan Africa shows the narrowest wage distribution, with relatively modest wages even for highly skilled employees.

The wage structure suggests that the potential economic gains from implementing GenAI in Western Europe could mirror those in the USA, while in Southern Europe, as well as in Central and Eastern Europe, the benefits would likely be more moderate. The MENA region presents a mixed picture: average wages are considerably lower than in the USA or Europe, suggesting a relatively lower potential for AI implementation. However, high wages of skilled individuals could represent a substantial opportunity for economic gains in labor market segments with significant AI applications. Sub-Saharan Africa may see more modest economic benefits stemming from AI implementation when compared with Europe and the USA, due to substantially lower labor costs.

Chapter 3

Mapping the future of work: estimating the labor market impact of AI across regions

Over the next 10 years, approximately 0.5%–5% of tasks can be profitably automated by GenAI, depending on the region.

In this chapter, we integrate the two elements explored in the preceding chapter: (1) the exposure of regional labor markets to AI, and (2) the economic benefits derived from this technology. We juxtapose these factors with the latest projections of the proportion of tasks likely to be automated through GenAI in the USA to evaluate the impact of GenAI on the labor market over the coming decade throughout the analyzed regions.

The approach

A recent article by Daron Acemoglu establishes a foundation for understanding AI's impact on the workforce. He starts by using AI task exposure scores provided by OpenAI researchers to estimate that nearly 20% of the US wage bill comprises tasks highly exposed to AI-driven automation. This estimate is consistent with prior findings from an EY report regarding the proportion of jobs with high AI exposure. Acemoglu then evaluates the cost-effectiveness of adopting AI for these exposed tasks over the next decade. Based on the research of Maja S. Svanberg and her co-authors at MIT and IBM, he assumes that about 23% of these tasks are likely to be automated both feasibly and profitably within this timeframe. Based on these calculations, Acemoglu predicts that roughly 4.6% of tasks in the USA could be automated or augmented using AI within 10 years, signaling notable economic advantages.

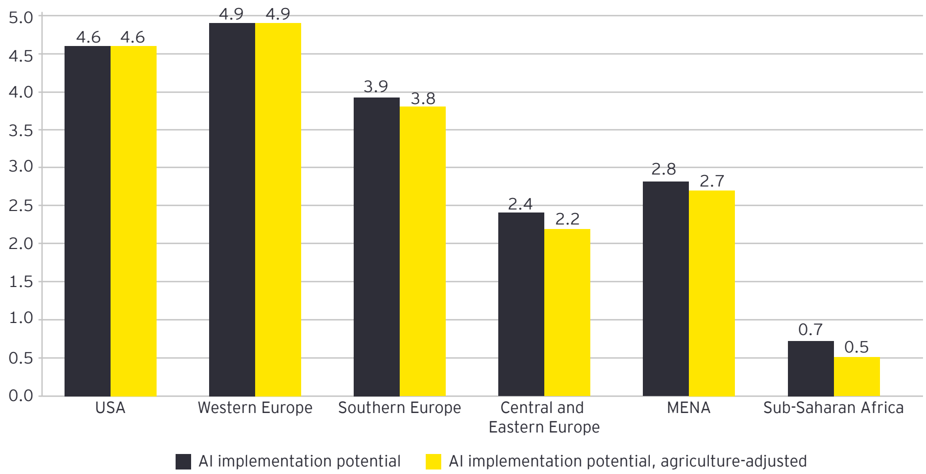
We replicate his approach for the USA and extend the analysis to other regions. To account for variations in AI's cost-effectiveness between regions, we adjust our estimates for relative wage levels. To be more precise, this adjustment reflects relative wages by country and occupation compared to their US counterparts, both expressed in terms of purchasing power parity. This means that the benefits of AI implementation are, for example, less pronounced in Sub-Saharan Africa, where average wages amount to less than 10% of the level recorded in the USA. In other words, the less expensive the labor, the weaker the gains from substituting or augmenting it with GenAI. At the same time, costs of AI adoption (average prices of software, hardware and work needed to implement GenAI) are assumed to be proportional to the general price level.

Our initial estimates are at the country-occupational level. To obtain results at the regional level, we aggregate these estimates based on the share of corresponding country-occupational pairs in the total regional wage bill. We provide two set of estimates: with and without adjustment for regional disparities in agricultural practices. The calculations suggest that over the next 10 years approximately 0.5%-5% of tasks can be automated by GenAI, depending on the region.

The USA and Western Europe lead the way[5]

The USA and Western Europe show similar AI implementation potential, with our estimates indicating that Western Europe may even slightly surpass the USA in AI adoption, with 4.9% of tasks expected to be managed by AI in the next decade compared to 4.6% in the USA. This advantage is due to comparable levels of AI exposure and slightly higher Western European wages in purchasing power terms, thus augmenting the economic benefits from AI implementation. It is worth noting, however, that our analysis does not account for a large concentration of technological firms leading AI innovation in the USA, which is likely to help it outpace Western Europe in AI implementation. This nuanced situation is echoed in the findings of this year's EY Europe Attractiveness Survey. While a majority of surveyed executives, 62%, acknowledge Europe's strength in having a workforce with the necessary technology skills – a crucial element for successful AI deployment – only 44% believe that Europe is actually ahead of other regions in implementing AI.

Figure 6: AI implementation potential, % of tasks in wage bill



Note: AI implementation potential considers AI exposure in specific regions and the economic feasibility of AI automation. The results for the USA are in line with estimates made by Daron Acemoglu. The differences observed in other regions are due to variations in labor market structures and wage levels. The term "Agriculture-adjusted" refers to estimates for AI adaptation where AI exposure is set to zero for agricultural occupations in Sub-Saharan Africa, MENA, Central and Eastern Europe, and Southern Europe.

Source: Acemoglu (2024), EY EAT.

5 Please note that our analysis omits countries such as China, which have led global AI patents since 2022. China also follows the USA and Western Europe in terms of the number of notable machine learning models and AI investments, which combined makes it prone to significant AI implementation in the forthcoming decade. and AI investments, which combined makes it prone to significant AI implementation in the forthcoming decade.

Southern Europe emerges as the third front-runner, predicted to see 3.8%–3.9% of tasks automated by AI, depending on assumptions regarding automation in agriculture. Here, despite a lower AI exposure than Central and Eastern Europe, higher wages tipped the scales. Central and Eastern Europe is projected to see approximately 2.2%-2.4% of its tasks automated by AI in the coming decade, a figure shaped by the region's moderate AI exposure and relatively lower wage cost.

MENA's AI implementation potential has been estimated to exceed that of Central and Eastern Europe, with 2.7%–2.8% of tasks projected to transition to AI. This is mainly due to high wages in selected country-occupational pairings that counterbalance the otherwise modest AI deployment potential. At the lower end of the adoption spectrum, Sub-Saharan Africa have anticipated AI task automation share of 0.7%, constrained by low wage levels relative to AI costs. The AI automation potential in Sub-Saharan Africa decreases to 0.5% when we exclude AI implementation in agriculture-related jobs.

Chapter 4

GenAI and the new economic era: business leaders' insights on the path to transformation

Practical steps for business leaders include: (1) seeking AI-driven efficiency increases, (2) embracing the opportunities and navigating the challenges in talent management presented by the advancement of AI, (3) account for international differences, and (4) monitoring the macroeconomic consequences of AI.

Advancements in GenAI are catalyzing a profound transformation in the business world. Here are practical steps business leaders can take to integrate AI into their operations:

1. **Cost reduction and quality improvement:** As highlighted by a recent EY CEO survey, CEOs are focusing on AI to drive growth and enhance productivity. By integrating AI into their operations, businesses can unlock significant cost savings – early studies indicate potential reductions ranging from 14% to 40%, coupled with an increase in the quality of work output. However, initial implementations are likely occurring in areas most amenable to AI, thus AI implementation benefits could prove to be more conservative when applied across the broader economy. Conduct a thorough cost-benefit analysis to identify which areas can yield the greatest returns from AI implementation.
2. **AI, talent acquisition, and talent development:** Executives and **professionals** see AI as an opportunity to speed up talent development. Promote how AI in your company enables employees to grow and access knowledge more rapidly, positioning your business as a desirable place to work. Be aware of public skepticism around AI and address these concerns proactively within your workforce. Openly discuss the potential impact of AI on jobs and implement policies that promote job security and reskilling opportunities.
3. **International dimension:** Be aware that a one-size-fits-all AI policy may not be most effective within multinational organizations – not only due to differences in tasks and jobs performed in various locations, but primarily due to wage differences which largely determine benefits from AI implementation. Focus AI investment on locations where tasks most exposed to GenAI are mainly performed and wage levels are relatively high.
4. **Productivity, investment, and industry impact:** Stay tuned for more in-depth information in our upcoming articles, as they will provide valuable insights into how AI can specifically enhance productivity in the economy, affect investment strategies, and have an impact on your industry.

Summary

The article offers insights into the GenAI impact on the labor markets of six analyzed regions: (1) Western Europe, (2) Southern Europe, (3) Central and Eastern Europe, (4) the Middle East and North Africa (together forming MENA), (5) Sub-Saharan Africa, and (6) the USA as a reference area. Combining exposure of occupations to AI with labor market structure and wage levels, we find that over the next 10 years approximately 5% of tasks can be automated or augmented in the USA and Western Europe, 4% in Southern Europe, 3% in the MENA region, 2% in Central and Eastern Europe, and 0.5% in Sub-Saharan Africa. Despite concerns, AI automatization could foster job creation and economic growth if we gear its development toward enhancing human capabilities. Executives and professionals are optimistic, with many seeing AI as a pathway to greater productivity and career advancement. In the following articles, we will delve deeper into AI's impact on productivity, investment, and industry-specific effects.

While the primary focus of our analysis did not consider the implications of the EU AI Act on the labor market, it is worth noting that the potential effects in this area are still under consideration. Future studies are necessary to comprehensively understand the impact of the EU AI Act on employment, job creation, and workforce dynamics within the EU and beyond.

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