Gen-AI and the Labour Market. Documents

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IMF Blog Post

AI Will Transform the Global Economy. Let's Make Sure It Benefits Humanity.

AI will affect almost 40 percent of jobs around the world, replacing some and complementing others. We need a careful balance of policies to tap its potential

Kristalina Georgieva, January 14, 2024

We are on the brink of a technological revolution that could jumpstart productivity, boost global growth and raise incomes around the world. Yet it could also replace jobs and deepen inequality.

The rapid advance of artificial intelligence has captivated the world, causing both excitement and alarm, and raising important questions about its potential impact on the global economy. The net effect is difficult to foresee, as AI will ripple through economies in complex ways. What we can say with some confidence is that we will need to come up with a set of policies to safely leverage the vast potential of AI for the bequnefit of humanity.

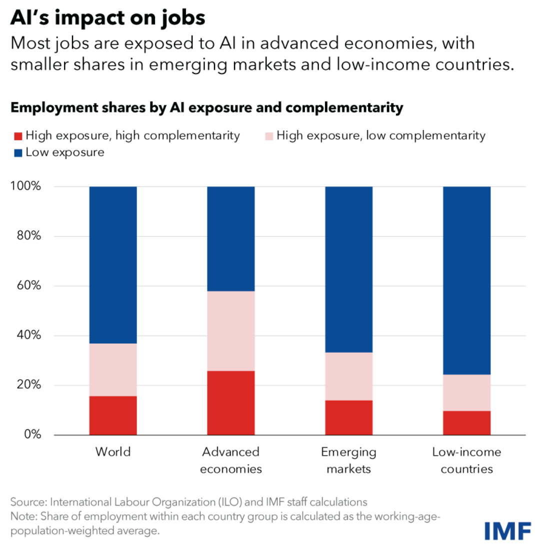
Reshaping the Nature of Work

In a new analysis, IMF staff examine the potential impact of AI on the global labor market. Many studies have predicted the likelihood that jobs will be replaced by AI. Yet we know that in many cases AI is likely to complement human work. The IMF analysis captures both these forces.

The findings are striking: almost 40 percent of global employment is exposed to AI. Historically, automation and information technology have tended to affect routine tasks, but one of the things that sets AI apart is its ability to impact high-skilled jobs. As a result, advanced economies face greater risks from AI—but also more opportunities to leverage its benefits—compared with emerging market and developing economies.

In advanced economies, about 60 percent of jobs may be impacted by AI. Roughly half the exposed jobs may benefit from AI integration, enhancing productivity. For the other half, AI applications may execute key tasks currently performed by humans, which could lower labor demand, leading to lower wages and reduced hiring. In the most extreme cases, some of these jobs may disappear.

In emerging markets and low-income countries, by contrast, AI exposure is expected to be 40 percent and 26 percent, respectively. These findings suggest emerging market and developing economies face fewer immediate disruptions from AI. At the same time, many of these countries don't have the infrastructure or skilled workforces to harness the benefits of AI, raising the risk that over time the technology could worsen inequality among nations.



AI could also affect income and wealth inequality within countries. We may see polarization within income brackets, with workers who can harness AI seeing an increase in their productivity and wages—and those who cannot falling behind. Research shows that AI can help less experienced workers enhance their productivity more quickly. Younger workers may find it easier to exploit opportunities, while older workers could struggle to adapt.

The effect on labor income will largely depend on the extent to which AI will complement high-income workers. If AI significantly complements higher-income workers, it may lead to a disproportionate increase in their labor income. Moreover, gains in productivity from firms that adopt AI will likely boost capital returns, which may also favor high earners. Both of these phenomena could exacerbate inequality.

In most scenarios, AI will likely worsen overall inequality, a troubling trend that policymakers must proactively address to prevent the technology from further stoking social tensions. It is crucial for countries to establish comprehensive social safety nets and offer retraining programs for vulnerable workers. In doing so, we can make the AI transition more inclusive, protecting livelihoods and curbing inequality.

An Inclusive AI-Driven World

AI is being integrated into businesses around the world at remarkable speed, underscoring the need for policymakers to act.

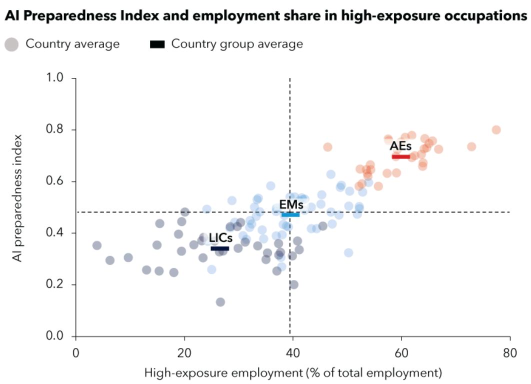
To help countries craft the right policies, the IMF has developed an AI Preparedness Index that measures readiness in areas such as digital infrastructure, human-capital and labor-market policies, innovation and economic integration, and regulation and ethics.

The human-capital and labor-market policies component, for example, evaluates elements such as years of schooling and job-market mobility, as well as the proportion of the population covered by social safety nets. The regulation and ethics component assesses the adaptability to digital business models of a country's legal framework and the presence of strong governance for effective enforcement.

Using the index, IMF staff assessed the readiness of 125 countries. The findings reveal that wealthier economies, including advanced and some emerging market economies, tend to be better equipped for AI adoption than low-income countries, though there is considerable variation across countries. Singapore, the United States and Denmark posted the highest scores on the index, based on their strong results in all four categories tracked.

Advanced-economy advantage

Wealthier countries often are better equipped for AI adoption.



Source: Fraser Institute, ILO, International Telecommunication Union, United Nations, Universal Postal Union, World Bank, World Economic Forum, and IMF staff calculations.
Note: Plot reflects 32 advanced economies, 56 emerging market economies, and 37 low-income countries. Dotted reference lines are derived from AI Preparedness Index median values and high-exposure employment.

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Guided by the insights from the AI Preparedness Index, advanced economies should prioritize AI innovation and integration while developing robust regulatory frameworks. This approach will cultivate a safe and responsible AI environment, helping maintain public trust. For emerging market and developing economies, the priority should be laying a strong foundation through investments in digital infrastructure and a digitally competent workforce.

The AI era is upon us, and it is still within our power to ensure it brings prosperity for all.

The Goal of the IMF

The IMF is a global organization that works to achieve sustainable growth and prosperity for all of its 190 member countries. It does so by supporting economic policies that promote financial stability and monetary cooperation, which are essential to increase productivity, job creation, and economic well-being.

From official website:

What kind of financial assistance does the IMF offer?

Unlike development banks, the IMF does not lend for specific projects. Instead, the IMF provides financial support to countries hit by crises to create breathing room as they implement policies that restore economic stability and growth. It also provides precautionary financing to help prevent crises. IMF lending is continuously refined to meet countries' changing needs.

Box 1. Artificial Intelligence Occupational Exposure and Potential Complementarity

Several studies have proposed definitions of AI exposure at the occupational level. The most common is the AI Occupational Exposure (AIOE) index of Felten, Raj, and Seamans (2021), measuring the correspondence between 10 AI applications and 52 human skills. This overlap between AI and human abilities is then weighted by the degree of importance and complexity of such skills in each job. This index is interpreted in relative terms and reported as normalized or rescaled between 0 and 1. It is also agnostic about the implication of exposure for human labor. In other words, it focuses on the relative likelihood of AI's integration into the functions of a given job, but it does not consider the likelihood of AI serving as a complementary technology or subsituting for human labor.

Some studies build on the AIOE measure to attempt to answer this question. Pizzinelli and others (2023) propose a potential complementarity index to adjust the original AIOE measure. In this approach, greater potential complementarity reduces exposure. Hence, a higher complementarity-adjusted AIOE (C-AIOE) more explicitly reflects a higher chance of labor substitution. To develop this index, the authors use O*NET, the same repository of occupational characterisitcs employed by Felten, Raj, and Seamans (2021), but draw from two different areas: work contexts and skills. Work contexts include social and physical aspects of how work in a given occupation is carried out. Using case-by-case judgment, the authors argue that in some contexts societies may be less likely to allow unsupervised use of AI. For instance, the criticality of decisions and the gravity of the consequences of errors are two job aspects that may motivate societies to require humans to make final decisions or take actions. Judges and doctors, for example, despite high AI exposure, would still likely be human beings.

Conceptually, exposure and complementarity can be thought of as two dimensions of relevance, as in Box Figure 1.1. At the first stage, exposure (*x*-axis) defines the scope for applying AI to carry out the main functions of a job. At the second stage, given the degree of potential application, a set of societal and technical concerns determines complementarity. For occupations with high exposure, low complementarity entails a relatively higher likelihood of AI replacing key tasks. In more acute cases, AI may lead to a decrease in the demand for the occupation altogether. This would in turn translate into reduced employment prospects, lower wages, and higher risk of displacment. High exposure combined with high complementarity entails a greater likelihood of workers in those jobs experiencing productivity growth and wage gains from adopting AI-driven technologies. However, these benefits will likely be contingent on possessing the skills needed to use AI. Without such skills, workers may be at a disadvantage and may experience lower compensation and reduced employment prospects. Last, at lower levels of exposure, complementarity becomes less relevant, because the tasks in an occupation that are likely to be either supported or replaced by AI are less integral components of the job itself (see Annex 2 for additional details).

Box Figure 1.1. Conceptual Diagram of AI Occupational Exposure (AIOE) and Complementarity (θ)

Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); and IMF staff calculations.
Note: Red reference lines denote the median of AIOE and compementaity.

This box was prepared by Carlo Pizzinelli.

Figure 1: This is an image

Working paper

Extract from Labor Market Exposure to AI: Cross-country Differences and Distributional Implications.* Prepared by Carlo Pizzinelli, Augustus Panton, Marina M. Tavares, Mauro Cazzaniga, Longji Li Authorized for distribution by Florence Jaumotte. October 2023 term is subsequently weighted and scaled by the ability's prevalence (L_{ji}) and importance (I_{ji}) within each occupation. This results in the AIOE for each occupation i. Details can be found in Felten et al. (2021).

As Felten et al. (2021) note, this measure focuses on "narrow" AI, which refers to "software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future." While this definition encompasses Generative AI, such as large language models and image generation, it does not capture exposure to "general" AI, which refers to computer software that can think and act autonomously and is combined with automation and robot technologies.

2.3 AI Exposure and Adjusting for Potential Complementarity

To construct our complementarity measure θ, we employ the same source of occupation-level data as Felten et al. (2021): the O*NET repository. We leverage two lesser used parts of the O*NET repository: work contexts and "job zones." O*NET's defines work context as the "physical and social factors that influence the nature of work." Out of the 57 contexts, we select 11 that we consider most relevant for the likelihood of AI replacing human activities or being adopted in a supervised manner, which we aggregate in 5 groups following O*NET's own grouping. The selection of these specific contexts, which we further discuss below, is motivated by the choices societies will plausibly make regarding the modalities of AI application or the likely need for supporting technologies (e.g., more advanced automation and robots) to fully implement AI in a given physical context.[8]

O*NET defines job zones as groups of occupations characterized by similar levels of education, on-the-job training, and professional experience needed to perform the work. The rationale for considering job zones is that occupations with longer periods of required professional development would have a greater ability to integrate AI knowledge into their training programs and thus equip future workers with complementary skills.

Together, the 11 contexts and the job zone are grouped into six components as follows:

1. **Communication**: i) Face-to-Face, ii) Public Speaking. As AI tools continue to evolve, they will undoubtedly enhance various aspects of communication. However, the subtle intricacies of face-to-face interactions and the art of public speaking largely remain the domain of humans. Societal norms may dictate the preservation of these sophisticated

[8]Tables A.1 and A.2 report all the work contexts from O*NET.

human communication skills in professional environments. For example, a trial lawyer employing rhetoric to persuade a jury or a physician explaining a diagnosis to a patient relies on nuanced understanding, empathy, and adaptability that AI currently cannot fully replicate. Moreover, in many circumstances, human interactions are affected by personal bias (for instance, based on gender or race). In these cases, AI can complement workers by attenuating their bias when carrying out essential in-person interactions that require lack of implicit influences.[9]

2. **Responsibility**: i) Responsibility for outcomes, ii) Responsibility for others' health. AI can certainly transform many sectors by augmenting tasks that bear significant responsibility for outcomes. Consider the healthcare sector, where AI assists with predictive analytics for patient risk or even the real-time monitoring of vital signs in critical care. Yet, the accountability and ethical decision-making inherent in these tasks demand human oversight, judgment, and, importantly, compassion. Even as AI capabilities expand, such responsibilities are likely to see a coexistence of AI and human labor, emphasizing complementarity over substitutability.

3. **Physical Conditions**: i) Exposure to Outdoors Environments, ii) Physical Proximity to Others. Roles necessitating substantial outdoor exposure and physical proximity require great level of adaptability and sensory acumen. These human skills are likely to continue to be invaluable in diverse professional contexts, such as the swift decision-making of a firefighter or the ability to operate in diverse environments of construction workers. Replacing these abilities and adaptability to conditions requires integrating AI technologies into highly advanced and costly machinery, suggesting greater likelihood of complementary co-existence of human labor and AI.

4. **Criticality**: i) Consequence of Errors, ii) Freedom of Decisions, iii) Frequency of Decisions. The critical importance of human oversight may become even more apparent to society as AI automates decision making processes over time. For instance, in professions such as air traffic controller or critical care nurses –which score high in these components– human judgment plays a vital role, relying on both data and instinct to act in often unexpected scenarios. At the same time AI can provide valuable data and suggestions, with the potential to reduce human error rates and speed up the time needed to make decisions.[10]

[9] A literature review by Hall et al. (2015) notes that many studies find significant levels of implicit bias by healthcare providers in the US towards certain ethnic groups "related to patient–provider interactions, treatment decisions, treatment adherence, and patient health outcomes."

[10] Good examples can be found in the use of AI to support radiologists in diagnostics, seeRajpurkar et al.

5. **Routine**: i) Degree of Automation, ii) Unstructured vs Structured Work. Occupations whose essential functions are easily codifiable in a set of routine actions have historically been substituted by technology to a greater degree (Autor et al., 2003; Autor, 2015; Autor et al., 2022). Despite the differences between AI and older forms of innovation, routine-intensive occupations reasonably remain more exposed to replacement, while less structured jobs may require more advanced technologies for AI to operate autonomously. For instance, telephone customer service assistants dealing with a large number of similar inquiries may follow routinized protocols of action which could be followed by software. Meanwhile, fashion designers, who score the lowest in automation and the highest in unstructured work, may use image-generation software or can leverage data-driven predictions on fashion trends, but they mostly work through a hard-to-codify creative process.

6. **Skills**: Job Zones. AI technologies demand a certain level of expertise to operate effectively, interpret outcomes accurately, and make informed decisions based on AI-generated insights. Occupations with already high education and long training requirements may have greater scope to integrate skills complementary to AI into their curricula. Although this reasoning is mainly applicable to future workers, who are yet to acquire the skills, these occupations also tend to feature regular training throughout workers' careers (e.g., summer schools for researchers, executive courses for managers, practical training, conferences).

Each work context in O*NET has a value between 0 to 100.[11] The automation score is inverted so that occupations with a low degree of automation have higher values to capture the fact that occupations that are already highly automated are more likely to face substitution as AI continues to advance. Job zones have an ordered categorical value from 1 to 5, which we multiply by 20 to convert into values from 20 to 100.[12] To align with Felten et al. (2021), the occupation classification in O*NET is converted to the US SOC 2010 classification.[13] This conversion ensures consistency and comparability between the

(2018), Sim et al. (2020), and Gaube et al. (2023)

[11] The original data source is available at https://www.onetonline.org/find/descriptor/browse/4.C/4.C.1/4.C.1.b

[12] Turning an ordinal variable into a cardinal variable has the implicit consequence of assuming a quantitative relationship, which may have non-trivial consequences. However, as also shown by the robustness checks below, the final complementarity index is not excessively sensitive to the "Skills" component relative to the other components.

[13] The US Bureau of Labor Statistics utilizes the Standard Occupational Classification (SOC) Code system at the 6-digit level, which has been updated in three editions: 2000, 2010, and 2018. O*NET utilizes a more granular 8-digit classification that is easily convertible to the SOC. This, in turn can be converted into the 4-digit ISCO-08, which can be applied to data from other countries.

two datasets for accurate analysis and interpretation. The score for each of the 6 groups is computed as the arithmetic mean of the scores of the individual contexts. Subsequently, θ is computed as the arithmetic mean of the six components and then divided by 100 to be bounded between 0 and 1. The lowest value, used as θ_{MIN}, is 0.31, corresponding to Hand Cutters and Trimmers (US SOC 2010 code 51-9031).[14] With the currently limited knowledge of how AI would be adopted in all sectors and jobs, taking the average of the various components represents a cautious stance regarding the relative importance of each factor. Moreover, while all components represent salient dimensions, none of them is necessarily applicable to all occupations. For instance, there may be occupations that, despite lengthy training processes, simply cannot integrate AI in their work in a complementary manner.

2.4 The Complementarity-Adjusted AIOE

Figure 2 plots the AIOE score against our measure of potential complementarity, consistent with our conceptual framework. Quadrants are segmented using the medians of both AIOE and complementarity θ, illustrating various interactions of AI exposure and complementarity. For instance, professions such as lawyers and judges, despite their high AI exposure, might harness AI as a valuable supporting tool. This would lead to productivity enhancements if they possess the requisite skills for this new tech interaction. In contrast, telemarketers, despite sharing a similar AI exposure level with lawyers, display minimal complementarity. This can be attributed to the fact that many of their duties, like detailing products or capturing customer data, can be easily taken over by AI applications. Occupations in the bottom left quadrant have both low exposure and low complementarity. Nonetheless, even within this group there may be some differences in the way workers could interact with AI. For instance, plausibly dancers could more easily leverage some form of AI application, as part of the creative process of their work, compared to dishwashers. Surgeons, although categorized in the low-AI exposure bracket, have the highest potential AI complementarity among all jobs analyzed. This can be attributed to the widespread adoption of AI in healthcare, particularly in areas like enhanced medical diagnostics.

Figure 3a) examines the distribution of potential complementarity and Felten et al. (2021)'s AIOE across broad occupations, categorized at the 1-digit ISCO-08 level. High-skill occupations such as managers, though as highly exposed to AI as clerical support workers, typically exhibit greater complementarity than their low-skill counterparts. Notably, a significant variability in complementarity exists within certain occupational groups, especially

[14] In contrast, the highest value of θ is 0.78, corresponding to Oral and Maxillofacial Surgeons (US SOC 2010 code 29-1022). The median value is 0.58.