**Generative AI and Jobs: Policies to Manage the Transition**

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**Abstract**

Advances in Generative Artificial Intelligence (GenAI) have shifted debates on automation away from manual work and routine tasks to concerns about the future of white-collar jobs and knowledge work. This brief, based on the ILO Working Paper 96, adds a global perspective to the debate, by providing income-based, regional and sub-regional estimates of occupational exposure. We stress that such potential does not imply full deployment and that, in practice, actual automation of tasks is likely to be lower than our estimated top threshold. Consequently, the main objective of the study is not to derive headline figures, but rather to analyse the direction of possible changes. Such insights are necessary for a proactive design of policies that can support orderly, fair, and consultative transitions.

The focus of this new analysis is on the “exposure” of occupations to GenAI. The study relies on a combination of AI and human judgement to identify tasks within 436 internationally standardized ISCO-08 occupations that could potentially be affected by technologies with capabilities similar to GPT-4 in the coming years. It subsequently draws on the ILO’s repository of harmonized country-level microdata to estimate global, income-based and regional shares of employment that fall into the conceptual categories of automation potential (most tasks could be replaced by GenAI) and augmentation potential (only some tasks are automatable, leaving a clear need for a human role).

**Occupational Exposure**

The study finds that clerical support workers are the most exposed occupational group: 24 per cent of the tasks in these jobs fall into high level of exposure to automation and another 58 per cent have medium-level exposure (Figure 1).

![Figure 1. Tasks with medium and high exposure to Generative AI, by occupational category](image)

Note: Occupational categories at ISCO-08 1-digit level. Levels of exposure to potential automation by GenAI with capabilities similar to GPT-4 on 0-1 scale. “Medium exposure” for 0.5-0.75 scores and “high exposure” for scores greater than 0.75.

Other occupational groups are less exposed, with only 1 to 4 per cent of tasks considered as having high automation potential, and medium-exposed tasks not exceeding 25 per cent. This means that, while certain tasks in these occupations could potentially be automated, most tasks still require human intervention. Such partial automation could enable efficiency gains, allowing humans to spend more time on other areas of work, thus “augmenting” their work.
These differences between occupational groups are well illustrated in Figure 2, which compares the distribution of task-level scores of automation potential found in the occupational categories of managers and clerical support workers. For managers, most occupations have score distribution somewhere on both sides of the medium exposure line of 0.5, with more tasks falling into low-level exposure. In contrast, for clerical support workers, many occupations have an entire score distribution that falls to the right of the medium exposure threshold of 0.5.

Exposed occupations as a share of employment

To derive a global estimate of exposed jobs, with breakdowns by country income group, gender and region, we apply the scores of automation and augmentation classifications to occupational distributions across countries, using ILO's harmonized microdata database.
Figure 3. Global estimates: jobs with augmentation and automation potential as share of total employment

Figure 3 shows jobs in augmentation (upper panel) and automation (lower panel) categories, calculated as a share of total employment at the global level and within country income groups. In global terms, the potential for augmentation is almost six times greater than it is for automation (13 per cent vs 2.3 per cent of total employment). High-income countries (HIC) are most exposed to automation risks: 5.1 per cent of their total employment is in this category, compared with 2.4 per cent in upper-middle-income countries (UMIC), 1.3 per cent in lower-income countries (LMIC) and 0.4 per cent in low-income countries. Across all income groups, women are more likely to be affected by automation than men.

Figure 4. Regional estimates: jobs with augmentation and automation potential as share of total employment
Conclusion and Policy Recommendations

Our findings largely align with the evolving body of academic literature concerning previous waves of technological transformations, but some of the trends we identify are new as a result of our exclusive focus on LLMs, and GPT more specifically. While early studies of potential AI adoption identified low-skill, repetitive and routine jobs as those with the highest potential of automation (e.g., McKinsey 2016; Frey and Osborne 2017), in which a computer-based system could be coupled with a machine to replace a human in manual production jobs (Autor 2015; Acemoglu and Restrepo 2020), more recent literature has highlighted the ability of Machine Learning systems to improve their performance in non-routine tasks (Brynjolfsson et al., 2018; Ernst et al., 2019; Webb 2019; Lane and Saint-Martin 2021). We argue that the emergence of LLMs reinforces this shifting picture, due to their refined ability to perform cognitive tasks, such as analysing text, drafting documents and messages, or searching through private repositories and the web for additional information. As a consequence, our study indicates that – at least in the short run – this new wave of automation will focus on a different group of workers, typically associated with “knowledge work” (Surawski 2019).

At the same time, our analysis shows that the most recent iteration of GenAI is unlikely to lead to the “end of work”. While the data on automation may seem alarming, especially when expressed in millions of jobs, it is important to note that potential exposure to GenAI is not equivalent to job loss. The occupational group with the highest share of tasks exposed to GenAI technology are the clerical jobs, and yet it is unlikely for all office jobs to disappear from one day to the next. In many countries, adoption may be constrained by unreliable access to or high cost of broadband and electricity, lack of digital skills needed to work with GenAI, as well as the cost of AI systems themselves. Such infrastructure constraints reveal the disparate challenges faced across the world.

While in high-income countries, the risk of automation applies to a higher share of employment and disproportionately affects women, such countries are also better equipped to deal with the cost of the transitions, both in financial and institutional terms. In low-income countries, the existing digital gap does offer a temporary shield from immediate exposure to automation, but it also creates a risk of missing out on the productivity benefits that generative AI has to offer.

As the potential share of global employment that could be “augmented” by GenAI is much greater, varying between 10-13 per cent across all country income groups, whether its effects on job quality are positive or negative hinges on the process of design and integration of AI systems at the workplace. While the technology could save human time for more engaging work, it can also be implemented in a way that worsens job quality. This would especially be the case if tools based on GenAI restrain worker autonomy, increase work intensity, or limit workers ability to provide feedback or discussion with management about the organization of their work.

Beyond the impact on existing employment, which is the focus of our study, new jobs are also likely to be created. While media discussions often focus on emerging, prestigious professions – such as prompt designers and AI content creators – it is essential that policies account for the most vulnerable workers in today’s supply chains of these AI systems. Creation of GenAI currently relies heavily on millions of human labourers who help develop the models through cleaning and tagging of their training data. Such workers often remain invisible, as the bulk of these assignments is conducted through crowdsourcing platforms, with workers hired as independent contractors, without the rights and benefits associated with an employment relationship. Ensuring that the new AI-related jobs are of good quality would help secure a potential source of positive employment opportunities for workers who may be displaced. Extending this focus on the entire supply chain of these GenAI systems would contribute to a more equal distribution of their benefits.

References


