Artificial Intelligence and Gender Inequality

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Extended Abstract

This paper sheds light on the potential impact of AI on gender inequality in regional EU labour markets. Because men and women sort into different jobs and sectors, a natural question is whether AI diffusion will have a differential impact by gender. Indeed, several studies highlight that AI could be a driver of both job displacement and new opportunities for women, depending on the specific nature of the work they do. For instance, both Brussevich et al. (2019) and Cortes and Pan (2019) show that women are disproportionately employed in occupations vulnerable to automation, and hence are at a higher risk of job displacement as compared to men. However, Cortés et al. (2024) suggest that women are more likely to transition to high-skill, high-wage occupations and Albanesi et al. (2025) and Pizzinelli et al. (2023) propose that AI can provide more job opportunities to, especially highly educated, women. Therefore, the impact of AI on gender inequality is likely to be mixed. Beyond its effect through the occupations held by the genders, one aspect that remains underexplored is whether the gendered effect of AI on labour market outcomes is compounded by sector and regional characteristics. As for the type of jobs men and women hold, the sectors in which they work clearly show segregation patterns. Additionally, the ability of regions to harness AI technologies is shaped by existing disparities in digital infrastructure, the level of skills of the labour force, institutional capacities and the regional innovation ecosystem. Therefore, regional disparities are likely to amplify the impact of AI of gender inequality. Understanding how AI influences gender inequality and, in particular, through which mechanisms is critical for policymakers to design targeted interventions and policies that reduce gender inequality. To conduct the analysis, we use a spatial general equilibrium model calibrated for the EU NUTS2 regions (RHOMOLO model) in which male and female workers are characterised by AI exposure levels across regions and sectors.

We first use four different occupation-specific AI exposure measures to simulate how the EU workforce is expected to evolve due to the integration of AI into occupations. The progress-based measure from Felten et al. (2018) reflects past AI developments from 2010 to 2015, focusing on tangible machine learning applications that have already influenced occupational tasks. The patent-based measure from Webb (2019) assesses the overlap between AI-related patents and occupational task descriptions using natural language processing, highlighting the extent to which patented AI technologies align with human-performed tasks. It provides an indicator of AI's capacity to replace or complement labour at the occupational level. The research-based measure from Tolan et al. (2021) takes a different approach by linking cognitive abilities to AI research intensity, measuring the extent to which current advancements in AI benchmarks correspond to essential occupational skills. Unlike the previous measures, this method does not directly map AI to tasks but instead incorporates an intermediate layer of cognitive abilities to assess its broader impact. Lastly, the expectation-based measure from Felten et al. (2021) adopts a forward-looking perspective by considering well-established AI applications, such as image recognition and language modelling, that are expected to shape workforce skills in the near future. We find that men and women are differentially exposed to AI. These differences mainly result from the fact that men and women work in different occupations and sectors, and occupations and sectors are differentially exposed to AI.

We then assess the impact of this AI exposure on disposable income by men and women, as well as on the gender employment and wage gaps, using the RHOMOLO model. This model is useful for scenario-based analysis, where shock are introduced to disturb the initial steady state derived from the 2017 interregional social accounting matrices. The resulting endogenous adjustments of key variables are interpreted as the effects of the simulated policies. To mimic the potential impact of AI on EU regional labour markets, we simulate both productivity and labour supply shocks. Consistent with the literature (Acemoglu and Restrepo (2019), Raj and Seamans (2018)), we use a positive productivity shock for workers with high AI exposure. However, given the current uncertainty about the overall impact of AI on labour supply, we consider two different scenarios: a labour-enhancing scenario, reflecting the potential for AI to augment human labour and create new job opportunities (Alekseeva et al. (2021), Damioli et al. (2023)), and a labour-replacing scenario, reflecting AI's potential to automate tasks and displace workers. Another key parameter in the model is the elasticity of labour substitution between men and women. Because men and women hold different type of positions, we consider that they are not perfectly substitutable at high and low levels of AI exposure. Bhalotra et al. (2021) find that the elasticity of substitution between male and female labor is around 2.6 in abstract task-intensive occupations, while it is approximately 1.2 in manual and routine task-intensive occupations. Therefore, we use the value of 1.2 for the elasticity of substitution at low levels of AI exposure and the value of 2.6 for the elasticity of substitution at high levels of AI exposure. Preliminary results suggest that, ceteris paribus, the integration of AI in the economy is expected to increase both the gender pay gap and the gender employment gap, as male workers are on average more exposed to AI than female workers. This overall effect masks regional and sectoral heterogeneity.

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