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EXPOSURE TO GENERATIVE ARTIFICIAL INTELLIGENCE IN THE EUROPEAN LABOUR MARKET

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We apply two sets of generative artificial intelligence (GenAI) occupational exposure scores – one task-based, one ability-based – to the European Labour Force Survey. While using different methodologies, our findings reveal consistent demographic patterns across the two approaches: jobs held by women, highly educated and younger workers are more exposed to GenAI technology in Europe. We also review the literature on the recent productivity impact of GenAI. Within the same occupations, less-experienced or less-skilled workers consistently get the largest productivity gains from GenAI support.

We argue that a task-based analysis is more fruitful than an ability-based one, both for guiding GenAI adoption in organisations and their workplaces, and for assessing the employment and job quality impact on workers.

Finally, we provide policy recommendations that can help workers (ie the labour supply) adjust to technological disruption, such as providing training and social safety nets. But we go further by also suggesting policy interventions that could redirect future labour demand towards better jobs, by promoting job redesign and organisational agility. Monitoring GenAI's employment effects and researching the 'jagged technological frontier' is necessary to further build our understanding of the employment impact of this transformational technology.

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1. Introduction

Until recently artificial intelligence (AI), in its rule-based or machine-learning (ML) forms, was only slowly spreading across organisations in Europe, reaching about 8 percent adoption in 2021 (Gotti *et al*, 2023). Diffusion of ML-based AI was slow in part because organisations needed a foundation of digital processes, data and infrastructure to support training of ML models on in-house data. When OpenAI released its ChatGPT chatbot at the end of 2022, a whole new type of 'plug-and-play' AI emerged to the public: 'pre-trained' models that users could directly interact with, using no or only a few training examples. These generative pre-trained transformers (GPTs) exposed the power of AI to the public at large. In a matter of seconds, users can now generate high-quality text, images, video and audio which would take human professionals days or weeks to produce.

While the technological potential seems large, the integration of generative AI (GenAI) into firms and organisations is only now beginning. As a 'general purpose technology' like electricity or computers, organisations need to figure out when, where and how they can use GenAI in their organisational (production) processes. For which tasks, processes, organisations and environments is it suitable? How can processes be redesigned to make the best use of GenAI? And what would that mean for jobs and workers?

In this paper, we take a dual approach to assess the impact of GenAI on the European labour market. First, we gauge the *potential impact* using occupational exposure scores, applied to the European Labour Force Survey. These scores calculate the 'exposure to GenAI' or the 'automatability using GenAI technology' in a theoretical sense, ie "*how exposed is an occupation to generative AI?*" While this does not tell us anything about actual GenAI adoption, it does give us an upper limit to the impact that could potentially be realised. Second, we assess the *actual impact so far* by reviewing the literature on the productivity impact of GenAI, both in experimental settings and in real-world workplaces and draw some conclusions from it. Next, we compare two types of methodologies for assessing GenAI impact on employment, the task-based and the ability-based approach and we point to missing perspectives in this literature. We conclude with policy recommendations.

2. The *potential* impact of GenAI on the European labour market

2.1. Overview of occupational (Gen)AI impact scores

Since Frey and Osborne (2017) first released their 'probability of computerisation' score, several more authors have produced similar exposure scores aimed at gauging the potential (or theoretical) impact of automation technology on occupations. Each of these authors make slightly different choices in the computation of their score, depending on: i) the level of analysis: a whole occupation, the tasks within an occupation or the abilities necessary to pursue the occupation; ii) the source of occupational information: job description databases, worker surveys or job vacancies; iii) the source of technological innovation: patent texts, technological performance benchmarks or judgements by experts, crowds or algorithms. Finally, iv) linking the sources on technological advancement and occupational characteristics can be done in several ways as well, using Natural Language Processing (NLP) in the case of patent texts, or using judgements by experts, crowds, or algorithms in the other cases.

The most known examples of automation impact scores include the following. Webb (2020) uses NLP to map patent texts to occupational task descriptions from the Occupational Information Network (O*NET) database[1] to calculate the technological exposure for each occupation. His approach is technology agnostic which allows him to apply it to several different technologies, like robots, software and AI. Autor *et al* (2022) take a similar approach as Webb (2020) but make the explicit distinction between automation technologies and augmenting technologies, again based on the patent text descriptions and titles. Brynjolfsson *et al* (2018) develop a rubric to assess the exposure of tasks to machine learning. They use crowdsourcing to apply the rubric to the Daily

[1] The Occupational Information Network (O*NET) is a comprehensive database and online resource that provides detailed information about various occupations. Developed and maintained by the U.S. Department of Labor, it describes occupations in terms of the knowledge, skills, and abilities required as well as how the work is performed in terms of tasks, work activities, and other descriptors.

Work Activities, a higher-level grouping of tasks, in the O*NET database. Felten *et al* (2021) also use crowdsourcing to link progress in AI benchmarks to work-related abilities at the occupational level, also from the O*NET database, to create an AI occupational exposure (AIOE) score. Tolan *et al* (2021) are the only ones to use surveys – EWCS[2] and PIAAC[3] – to assess the occupational impact of AI. They use expert judgement to link AI benchmarks to cognitive abilities on the one hand and cognitive abilities to survey-based occupational task intensity on the other hand. Their approach is the only one that allows for variation within occupations, as survey respondents might have different experiences within the same occupation. Finally, Lassébie and Quintini (2022) also used expert judgements to assess the automatability of skills and abilities within occupations.

In this paper we focus on a specific subset of automation and AI technologies, namely *generative* AI or Generative Pre-trained Transformers (GPT), meaning foundational models that can produce text, images, audio and video. To our knowledge, only three papers so far explicitly focus on generative AI. The first one is a refinement by Felten *et al* (2023a) of their earlier AI occupational exposure (AIOE) mentioned above. To refine their general AIOE to the context of *generative* AI, they only use 2 of their original 10 AI benchmarks: the one for language modelling (or the ability to model, predict or mimic human language) and the one for image generation (or the creation of complex images). This produces two additional scores, next to the general AIOE score: a language modelling occupational exposure (LMOE) score and an image generation occupational exposure (IMOE) score. The second paper focusing on generative AI is by Eloundou *et al* (2023) in which they calculate a 'GPT occupational exposure' in a very similar way as Brynjolfsson *et al* (2018) above but focusing the rubric not on machine learning but on GPT technology. Interestingly, next to using human ratings (crowdsourced) to apply the rubric to work activities, they also use GPT-4 to rate the GPT-exposure of the tasks and daily work activities. This means that they both ask people as well as GPT-4 whether a task could be completed in half the time using GPT technology. Finally, Gmyrek *et al* (2023) from the International Labour Organisation (ILO) take a similar approach to Eloundou *et al* (2023) but they use the internationally applicable International Standard Classification of Occupations (ISCO) taxonomy as a basis to apply their rubric to, instead of the American O*NET database. Given that the scores by Eloundou *et al* (2023) have not yet been made public at the time of writing, our paper will focus on comparing the general AI, the LM and IG scores from Felten *et al* (2023a) with Gmyrek *et al's* (2023) ILO exposure score. In the next section, we give more detail about the construction of these scores and use them for our analysis of generative AI's impact on the European labour markets.

2.2. Applying generative AI exposure scores to EU-LFS

To study the effect of generative AI on the European labour market we use the exposure scores computed by Felten *et al* (2023a) and by Gmyrek *et al* (2023).

The first use the methodology described in Felten *et al* (2021) to determine the occupations most exposed to advances in i) AI and more specifically in ii) language modelling and iii) image generation. This approach links ten AI applications (such as image generation, language modelling, abstract strategy games, real-time video games) to 52 human work-related abilities (such as oral comprehension, oral expression, inductive reasoning etc). The 52 abilities are then linked to more than 800 occupations using the O*NET database. The O*NET database provides weights for each ability in each occupation describing its importance and its level needed for that occupation, which the authors use to calculate weighted mean exposure scores across abilities within occupations. In this paper, our attention is centred on the exposure to *generative AI*. Therefore, we delve into the exposure scores that are tailored to two specific applications of AI: language modelling occupational exposure (LMOE) and image generation occupational exposure (IGOE). These scores are described in Felten *et al* (2023a).

Gmyrek *et al* (2023), our second source of generative AI exposure scores, build upon the method recently demonstrated by Eloundou *et al* (2023). Gmyrek *et al* (2023) start from the International Standard Classification of Occupations (ISCO-08), which contains a list of tasks associated with each occupation. The

[2] Eurofound's European Working Conditions Survey.
[3] OECD's Survey of Adult Skills in its Programme for the International Assessment of Adult Competencies

authors then ask GPT-4 to give a score of potential automation for each task. Contrary to the O*NET database, the ISCO classification does not contain weights for each task, so the authors apply equal weights when aggregating the automatability scores to the occupational level.

Table 1 below compares the two approaches – Felten *et al* (2023a)'s ability-based and Gmyrek *et al* (2023)'s task-based approach – for one occupation, namely primary school teachers, which is ISCO occupation 2341 and SOC occupation 25-2021.

Table 1: Comparison of ability-based and task-based approaches to calculating occupational AI exposure for primary school teachers

ABILITY-BASED **Felten *et al* (2023a)**				**TASK-BASED** **Gmyrek *et al* (2023)**	
25-2021 - elementary school teachers, except special ed.				**2341 - Primary school teacher**	
O*NET Ability	**Importance**	**LM exposure**	**IG exposure**	**ISCO Task**	**Automa-tability**
Oral Expression	91	0.91	0.37	Preparing daily and longer-term lesson plans in accordance with curriculum guidelines;	0.60
Oral Comprehension	75	0.91	0.41	Instructing children individually and in groups, using various teaching methods and materials (eg computers, books, games), adapting to children's varying needs;	0.30
Written Comprehension	75	0.83	0.47	Maintaining discipline and good working habits in the classroom;	0.15
Written Expression	75	0.85	0.47	Planning and conduct activities with the children such as sporting activities, concerts and excursions;	0.25
Problem Sensitivity	75	0.59	0.55	Participating in staff meetings and other sessions, and conferring with other teachers concerning educational issues;	0.15

Source: Gmyrek *et al* (2023), Felten *et al* (2023a)'s AIOE_DataAppendix.xlsx available on Github (https://github.com/AIOE-Data/AIOE) and O*NET Online database. Only a selection of the associated abilities and tasks are shown for each approach.

To examine how exposed the European labour market and its workers are to generative AI, we merge Felten *et al* (2023a) and Gmyrek *et al* (2023) occupational exposure scores to the European Labour Force Survey (EU-LFS). We first aggregate employment data at the country level from the 2022 wave of the EU-LFS and subsequently merge it with the exposure scores using the ISCO classification system.

Labour market data. The EU-LFS serves as one of the most extensive and comprehensive resources for conducting large-scale research on the European labour market. It is conducted by national statistical institutes throughout Europe, which oversee survey administration, sample selection, questionnaire preparation, direct household interviews and forward the results to Eurostat. The survey's objective is to categorise the working-age population (15 years and older) into three distinct and exhaustive groups: employed individuals (including self-employed), unemployed individuals (together forming the 'labour force') and those outside the labour force. Our main sample is composed of persons older than 15 that are employed and that live in one of the 27 European countries. Given the absence of the three-digit level occupation variable for Bulgaria, Slovenia, and Malta, our analysis omits these countries, allowing us to concentrate solely on the remaining 24. We use the provided survey weights to ensure the weighted sample accurately represents the target population.

Occupational scores. Scores obtained from Felten *et al* (2023a) are originally designated for the US-specific Standard Occupational Classification (SOC) system. However, our employment micro-data, uses the International Standard Classification of Occupations (ISCO), which requires aligning these classifications. We achieve this alignment using the SOC-2010 to ISCO-08 crosswalk provided by the American Bureau of Labor Statistics. The conversion occurs at the four-digit ISCO level, but we average the scores at the three-digit level[4],

[4] This assumes that each 4-digit occupation has an equal share within their respective 3-digit occupational group.

which is the level that is available in the EU-LFS. The validity of our generative AI exposure measures, converted from an US to an EU setting, depend on the following two assumptions. First, we assume that occupations in the EU require similar work-related abilities as those in the US. This assumption depends on the similarity of task content of jobs across the Atlantic and well as similarities in the organisation of work. Second, we assume that work-related abilities in EU countries are similarly exposed to GenAI technology as in the US. Given the widespread, online availability of GenAI applications like ChatGPT, DALLE-3 and Midjourney, this second assumption seems very reasonable. Similarly, Gmyrek *et al* (2023) provide occupational exposure scores at the four-digit ISCO level, but we average the scores at the three-digit level. It should be underlined that the exposure scores from Felten *et al* (2023a) are standardised and normalised and thus positive exposure scores suggest above-average values, while negative scores suggest below-average values. The ILO exposure score from Gmyrek *et al* (2023), representing potential automation, is rated on a scale of 0 to 1, where values closer to 1 indicate higher susceptibility to automation. From now on, the AI occupational exposure (AIOE), language modeling occupational exposure (LMOE), and image generation occupational exposure (IGOE) introduced by Felten *et al* (2023a) will be denoted as AI, LM and IG, respectively, while the occupational exposure score from Gmyrek *et al* (2023) will be referred to as ILO.

From Felten *et al* (2023b) we know that the occupations that are most exposed to advances in language modelling heavily rely on language- and communication-related abilities, such as telemarketers and a wide variety of education-related occupations. Furthermore, many of the occupations most exposed to advances in image generation are occupations where spatial orientation is important, such as interior designers and architects. Before delving into more detailed findings, an examination of the raw exposure scores indicates that, on average, occupational exposure to language modelling surpasses that of image generation (confirmed by a significant t-test of means at $p < 0.01$). This observation implies that abilities most influenced by advancements in language modelling – such as communication and language-based skills – are more prevalent, or in other words are more common in jobs, compared to those most impacted by advancements in image generation technologies, specifically visual or spatial abilities. In the study by Gmyrek *et al* (2023), they find that clerical tasks have the highest exposure to GenAI when compared with other tasks. They thus find that the broad occupation of clerical work is the most exposed to generative AI. In Table A3 of the Appendix A, the top and bottom fifteen ISCO occupations by GenAI measures are presented. When analysing the ISCO occupations at the two-digit level in Table A4, it becomes evident that the broad category "41 General and Keyboard Clerks" is the only category present in the top 5 for the two different sources of exposure scores. Specifically, it holds a position in the top 5 for both the ILO exposure score and the LM exposure score. The notable differences in occupational exposure scores between the two sources, Felten *et al* (2023a) and Gmyrek *et al* (2023), might be explained by variations in their computational methodologies. Finally, while the two sets of scores do not rank the occupations by exposure in the exact same order, they do correlate quite a bit: the general AIOE score by Felten et al and the ILO's score show a Pearson correlation of 0.78 and Spearman rank correlation of 0.82.

2.3. Distributional impact of generative AI on European labour markets

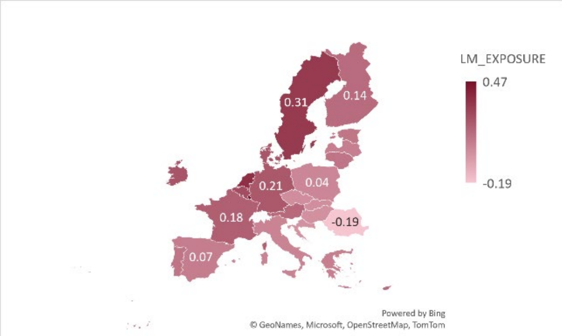
We explore the variation in generative AI exposure across countries, gender, age groups, educational attainment, urbanisation and uptake of remote work. We also explore the variation of generative AI exposure in occupational employment across recent years. Throughout the whole analysis, it's important to note the neutrality of Felten *et al* (2023a) regarding whether exposure to generative AI in occupations leans toward automation or augmentation. So, while we cannot say whether high exposure will lead to more or less employment, we can say that high exposure likely means large disruptions to the content and organisation of work and with that severe uncertainty in impacted demographic groups.

2.3.1. By country

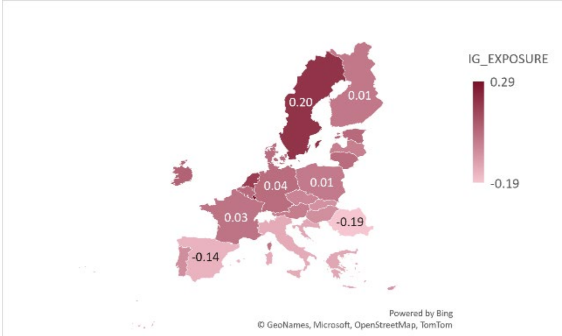
As we examine national exposure to generative AI, both a north-south and an east-west divide emerges, when using Felten *et al* (2023a) scores. With northern European countries such as the Netherlands, Denmark and Sweden displaying higher exposure compared to their southern counterparts like Spain, Greece and Romania. This trend holds true not only for the overarching AI measure but also for the specific measures related to image generation and language modelling as can be seen in Figure 1. The disparity lies in the magnitude of exposure, which is more pronounced for language modelling than for image generation. When using the ILO score, there does not seem to be a clear north-south division. Instead, our exposure map of the ILO score shows that high-income countries are more exposed to generative AI, with countries like the Netherlands and Germany having higher exposure scores. For a more comprehensive breakdown of exposure scores by country for each of these exposure scores, refer to Table A1 in the Appendix A for detailed information.

Figure 1. Generative AI exposure by country in Europe

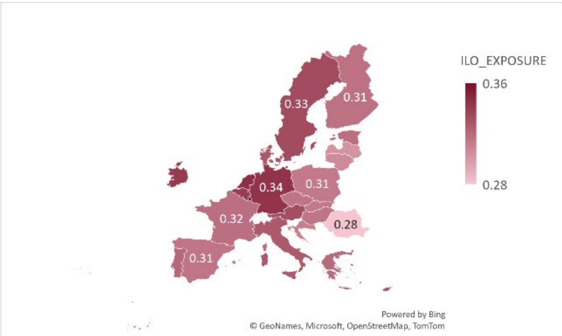
Panel A. Exposure to Language Modelling



Panel B. Exposure to Image Generation



Panel C. ILO Exposure



Source: EU-LFS (2022) and Felten *et al* (2023a. Source: EU-LFS (2022) and Gmyrek *et al* (2023)

2.3.2. **By gender**

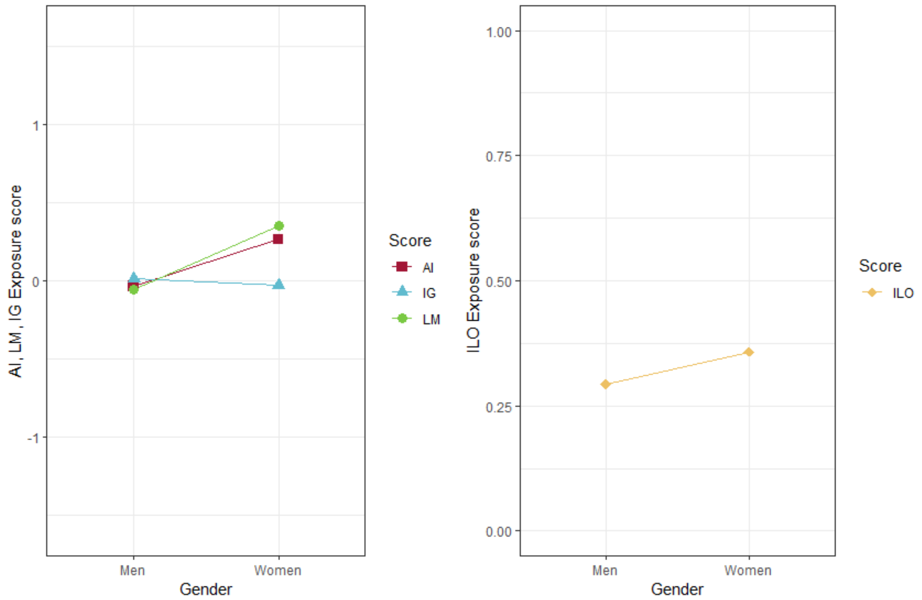
Variations in the impact of generative AI technologies on different occupations can have a distinct impact on labour market outcomes for men and women. This is particularly true given that the distribution of individuals across occupations varies by gender. To illustrate, we computed average exposure scores for AI, LM, IG and ILO across gender in Europe. We find that women, on average, experience a higher exposure to generative AI. Raw exposure scores indicate that female workers, on average, have occupational exposure scores to AI, LM and ILO exceeding those of their male counterparts (shown by significant t-tests of means at $p < 0.01$). From the Felten *et al* (2023a) exposure scores, the results suggest that abilities most influenced by advancements in AI and LM are more commonly found in jobs held by women. This is also true for the task-based approach that the ILO took: tasks typically held by women are more exposed to GenAI. The substantial difference in the average LM score, which is substantially higher for women (0.35) compared to men (-0.05), is especially remarkable. Figure 2 also shows that the ranking of AI exposure scores differs by gender, with women having a higher likelihood of exposure to LM, followed by AI in general and then IG. Conversely, men exhibit the opposite trend, with a higher average exposure to IG, followed by AI in general and then LM.[5] It should be noted that both AI and LM average

[5] These results should be interpreted with caution given that they are based on averages and are highly influenced by outliers. Figure A1 in Appendix A reveals a notable discrepancy in the standard deviation of exposure scores. In general, all standard deviations are high indicating a greater dispersion of values from the mean.

exposure scores for men taken from Felten *et al* (2023a) are negative and thus indicates values below the mean.

When examining the correlation coefficients between the percentage of female or male workers in each occupation and their corresponding exposure scores, we observe a positive correlation for female workers and a negative correlation for male workers. Thus, occupations with a higher proportion of female employees tend to have higher exposure scores. This trend is the most pronounced when considering the LM and ILO score[6]. Among the top 10 occupations with the highest LM scores and substantial proportions of women, we find: Legal professionals, Social and religious professionals, Finance professionals, Authors and journalists and linguists, Secretaries (general), General office clerks, Secondary education teachers. Similarly, among the top 10 occupations with the highest ILO scores and substantial proportions of women, there are: Keyboard operators, General office clerks, Client information workers, Numerical clerks, Secretaries (general), Authors, journalists and linguists, Other clerical support workers, Administrative and specialised secretaries, Librarians, archivists and curators. The positive correlation points to occupational segregation, indicating that women are disproportionately concentrated in occupations with higher levels of (gen)AI exposure. It is quite remarkable that the most-exposed occupations identified by both Felten *et al* (2023a) and Gmyrek *et al* (2003) have high concentrations of women, given that these two sets of authors use wildly different methodologies and data sources.

Figure 2. Generative AI exposure by gender in Europe



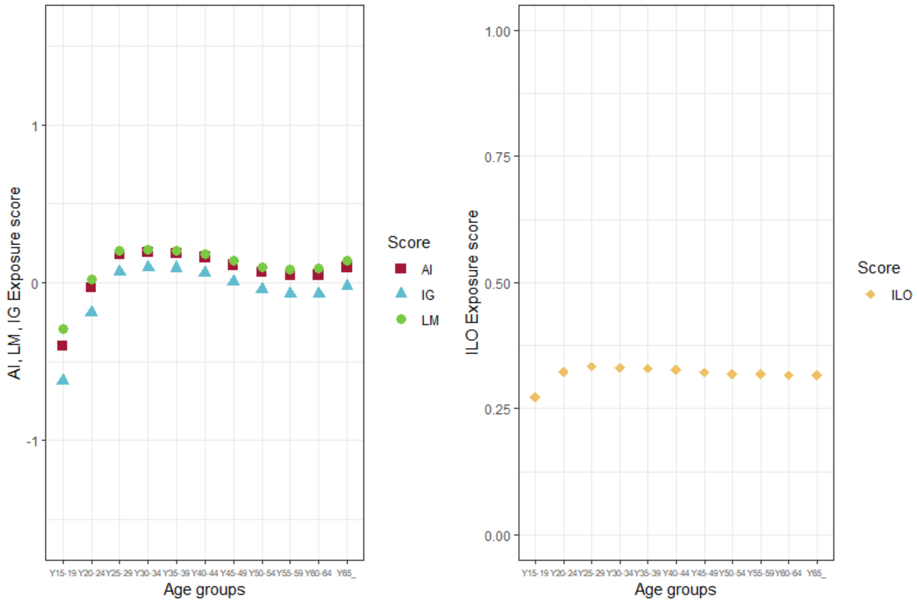
Source: EU-LFS (2022), Felten *et al* (2023a) and Gmyrek *et al* (2023)

2.3.3. By age groups

Similarly to gender, demographic distribution across occupations could lead to differential exposure to GenAI across age groups. The analysis by age reveals that individuals in the age range of 25-44 exhibit, on average, higher exposure scores. This means that individuals in this age group are disproportionally more represented in occupations that are more exposed to generative AI. This is not due to a gender composition as Table A2 in the Appendix shows that there is no overrepresentation of women in the 25-44 age categories that could account for these results. The left-hand side of Figure 3, using the Felten *et al* (2023a) scores, shows that across all age groups, the pattern of AI exposure ranking remains consistent, with a higher likelihood of exposure to LM, followed by AI and then IG. It's noteworthy that despite being calculated using different methods, the exposure scores from the two distinct sources exhibit similar patterns throughout the age distribution.

[6] The correlation coefficient, which corresponds to the correlation between the share of female employment in an occupation and the associated technology exposure measure, is 0.44 for the LM score and 0.37 for the ILO score.

Figure 3. Generative AI exposure by age groups in Europe



Source: EU-LFS (2022), Felten *et al* (2023a) and Gmyrek *et al* (2023)

2.3.4. **By educational attainment**

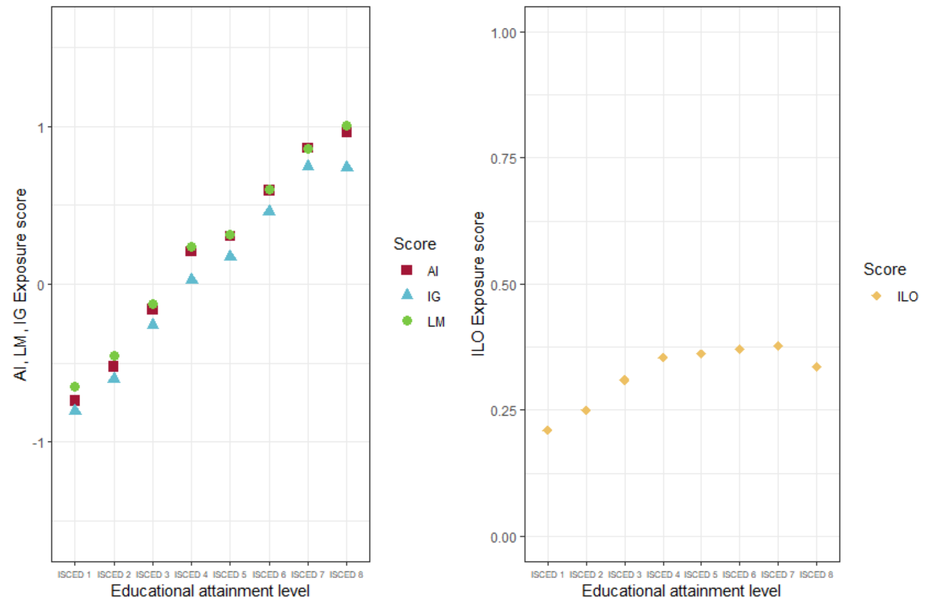
To investigate whether advances in generative AI are particularly likely to affect highly educated workers, we evaluate the correlation between the exposure measures and the highest level of education successfully completed. Figure 4 indicates a positive correlation between the exposure scores and the highest level of education attained. Potential exposure to generative AI systematically increases with each ISCED level for the three scores computed by Felten *et al* (2023a). The ILO score also experience a positive but a slightly less steep increase with each ISCED level and a decrease for ISCED level 8. We will be the first ones to analyse the average ILO exposure score by educational attainment as this was not analysed by Gmyrek *et al* (2023). Our findings align with the ones of Felten *et al* (2023a) and Cazzaniga *et al* (2024), that highly educated individuals are more susceptible to exposure to advancements in generative AI technologies. As stated above, it's important to note the neutrality of Felten *et al* (2023a) regarding whether exposure to generative AI in occupations leans toward automation or augmentation.

So far, the dominant theories explaining the impact of technology on the labour market have been the Skill Biased Technological Change (SBTC) and Routine Biased Technical Change (RBTC). The SBTC theory suggests that technological advancements disproportionately boost the productivity of highly educated workers, leading to an increased demand for their skills. This phenomenon was identified as a key driver of the growing wage inequality that began in the late 1970s in the US, according to studies by Autor *et al* (1998), Autor and Katz (1999), Acemoglu (2002) and Krueger (1993).

However, criticisms of SBTC have emerged, particularly from studies like Card and Di Nardo (2002), which argued that SBTC fails to explain gender and racial wage gaps or variations in the return to education for different demographic groups. Additionally, wage and job polarisation accelerated as medium-skilled workers in routine-intensive jobs were displaced, giving rise to the RBTC theory. Autor *et al* (2003) demonstrated in an influential paper that computer capital complements for workers at the extremes of the wage distribution in non-routine problem solving and complex communication tasks but substitutes for medium-skilled workers in routine cognitive and manual tasks. Subsequent studies, including Goos and Manning (2007), Acemoglu and Autor (2011), Autor and Dorn (2013) and Cortes *et al* (2017) have supported and expanded upon the RBTC theory.

The focus of our paper is on the more recent period marked by the rise of AI, especially generative AI. As a general-purpose technology with the potential to impact virtually every occupation, AI has revived discussions about the effects of technology on employment. The automation of non-routine tasks, typically carried out by highly skilled workers, introduces a new dimension to the SBTC theory, as illustrated by Albanesi *et al* (2023).

Figure 4. Generative AI exposure by educational attainment

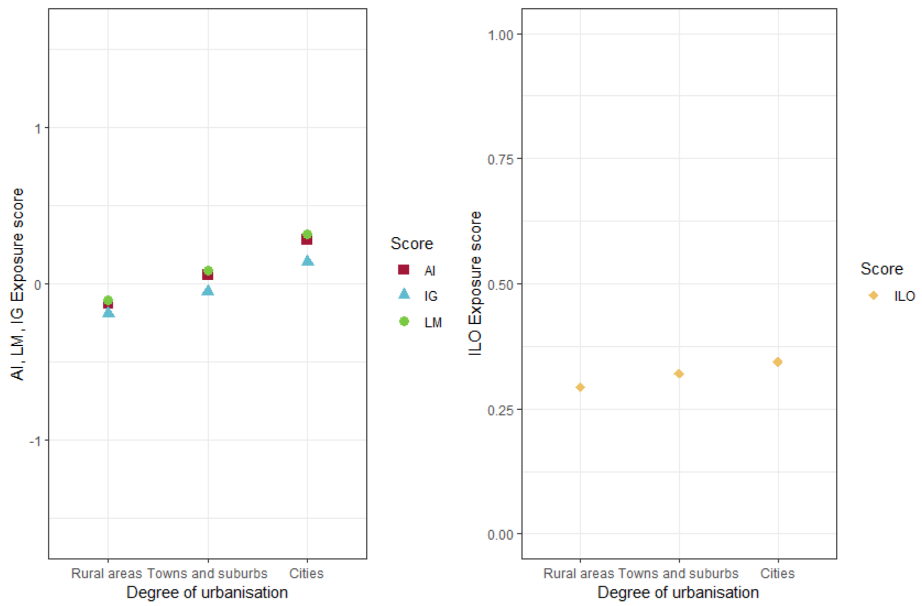


Source: EU-LFS (2022), Felten *et al* (2023a) and Gmyrek *et al* (2023)

2.3.5. **By degree of urbanisation and remote work**

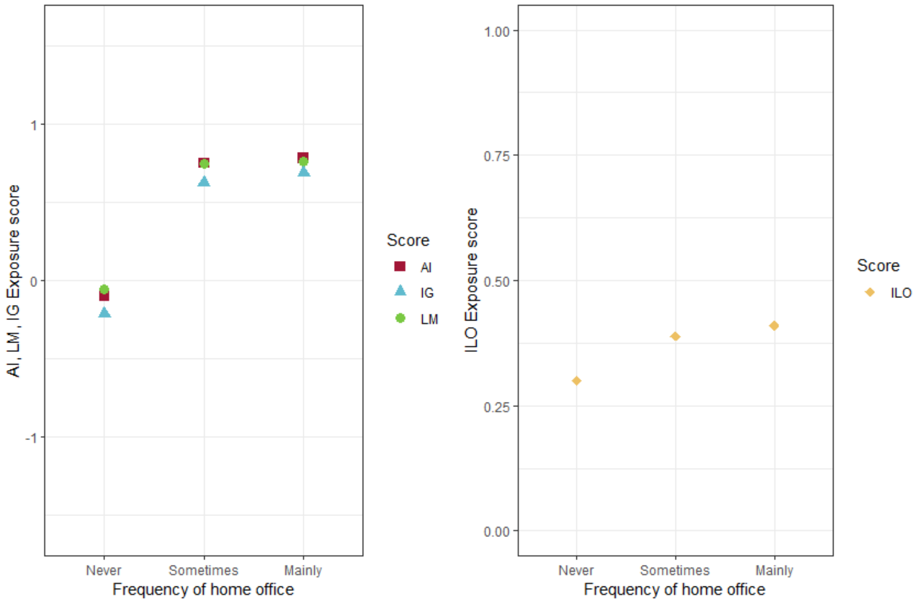
Additionally, we explore two other dimensions: the average exposure of generative AI based on the degree of urbanisation and the frequency of remote work. The findings suggest that individuals residing in urban areas and those predominantly working from home are more exposed to generative AI technologies.

Figure 5. Generative AI exposure by degree of urbanisation



Source: EU-LFS (2022), Felten *et al* (2023a) and Gmyrek *et al* (2023)

Figure 6. Generative AI exposure by frequency of remote work



Source: EU-LFS (2022), Felten *et al* (2023a) and Gmyrek *et al* (2023)

The observed patterns in occupational exposure to generative AI by urbanisation and remote work could be explained by several factors: i) cities are hubs for innovation and technology-driven sectors, which may lead to higher exposure to generative AI in urban occupations, ii) individuals who primarily work from home may use technology more intensively. Generative AI technologies, which often involve language or image processing, could be more integrated into remote work scenarios, leading to higher exposure. These explanations are speculative and would benefit from a more in-depth analysis of the specific industries, occupations and technological contexts within urban and remote work settings. Our data also shows that remote work is taken up more in cities compared to rural areas. These findings align with Stephany's (2022) results, indicating that even though online jobs can be completed in the lowest-cost locations (rural areas), they are mainly done by workers in large cities. This result may also be driven by the fact that jobs without remote work options are predominantly manual, often found in sectors like manufacturing, which frequently operates outside urban areas.

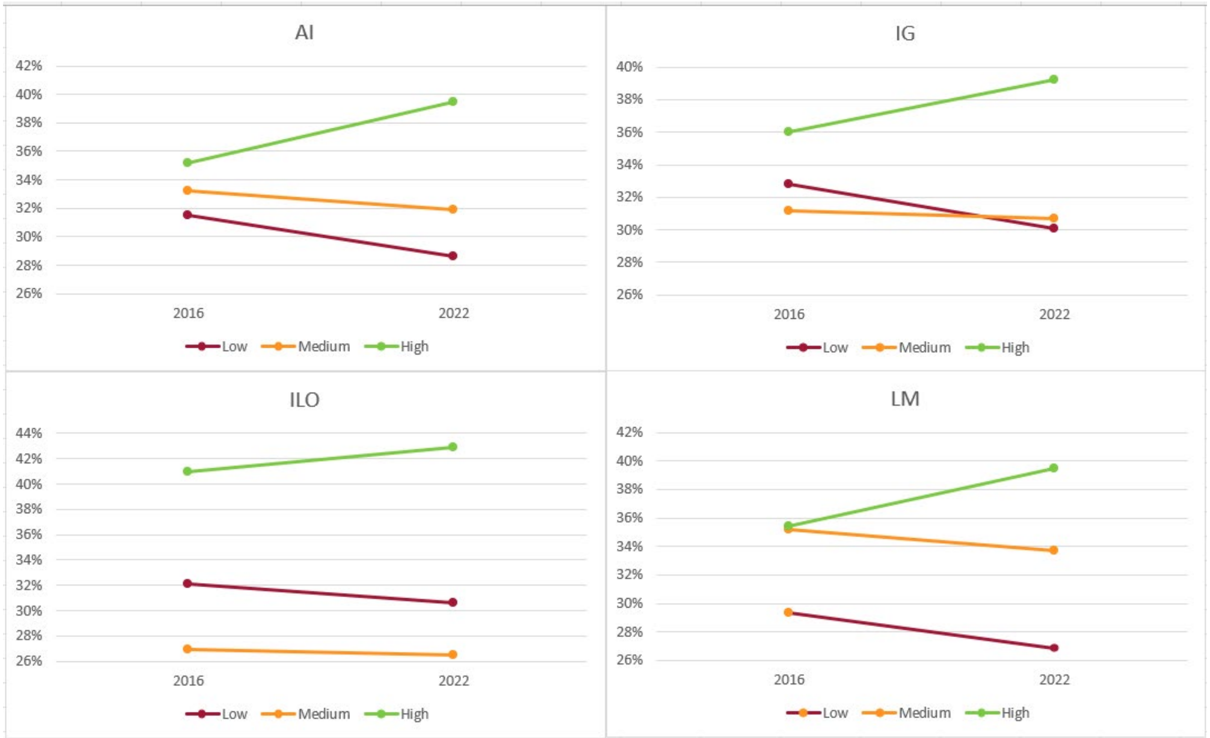
We have identified comparable demographic trends in our analysis of exposure scores from two distinct sources. While the highest exposed occupations differ between the two sources, there is a consistent trend: women, younger workers and more skilled individuals tend to be in occupations with higher exposure.

2.3.6. **By year**

Next, we investigate the changing distribution of employment across GenAI-exposed occupations at the three-digit level from 2016 to 2022[7]. We categorise occupations into terciles based on their GenAI exposure, dividing them into low, medium and high exposed groups. As the exposure scores are fixed over time, the categorisation of occupations stays constant and we calculate the employment share within each tercile. Between 2016 and 2022, there is a notable rise in employment shares within the high exposure group, while the low and medium exposure groups experience a decrease.

[7] For a detailed breakdown of changes in employment shares based on age groups and gender, refer to Appendix B. Appendix B also provides detailed information on employment shares within each tercile for every score in each country studied, as illustrated in Figure B4, Figure B5, Figure B6, and Figure B7.

Figure 8. Employment shares by GenAI exposure terciles



Notes: Y-axis indicates average annual employment shares. Exposure score categories (low, medium, high) reflect terciles of the respective technology measure's scores.

2.3.7. Conclusion of exposure analysis

To conclude, it is worth emphasising that in this analysis the importance lies not necessarily in the precision of the estimates but in the broader distribution among demographics. By applying (gen)AI exposure scores from two distinct sources to the EU-LFS, we note that, on average, women, younger individuals and those with higher education levels tend to be more exposed. This finding is consistent with the results reported in a recent IMF report by Cazzaniga *et al* (2024). Moreover, individuals engaged in remote work, residents of urban areas and workers in higher income countries demonstrate higher levels of exposure. Additionally, there appears to be a very light positive upward trend in the employment share within occupations that exhibit higher levels of exposure.

Finally, it is quite remarkable that the two sets of scores are similarly distributed across demographics like gender, age and education, even though they originate from different occupational data sources and use very different methodologies.

3. The *actual* impact of generative AI so far

The figures above illustrate how demographic groups may be differentially exposed to – and thus may experience differential impact of – generative AI. The implications for economic inequality will depend on when and under what conditions such technologies are likely to automate versus augment which types of labour. In this section, we review the scientific evidence on the actual impact of generative AI so far, both in experimental settings and in real-world work environments.

Previous automation technologies – like robots and information technology – mainly served as a complement to higher-skilled workers, while reducing employment in occupations containing mostly routine tasks, like machine operators and administrative assistants (Autor *et al*, 2003; Bresnahan *et al*, 2002; Bartel *et al*, 2007; Acemoglu and Restrepo, 2020). Generative AI however has the potential to also impact non-routine task occupations, such as teachers and designers (Felten *et al,* 2023a). Existent observational and experimental studies of generative AI draw two clear conclusions: GenAI can increase productivity in complex analytic, non-routine tasks (like writing, coding, customer support, ideation and research), but gains predominantly favour individuals with lower or medium levels of experience, skill, or productivity (Noy and Zhang, 2023; Dell'Acqua *et al*, 2023; Peng *et al*, 2023; Brynjolfsson *et al*, 2023).

3.1. Generative AI in experimental settings

In experiments, generative AI is found to directly enhance writing (Noy and Zhang, 2023) and programming (Peng *et al*, 2023). Additionally, it has shown positive impacts on ideation and creative work (Boussioux *et al*, 2023; Girotra *et al*, 2023; De Cremer *et al*, 2023). These experiments support the claim of the exposure literature above that creative, highly paid and highly educated workers will be most impacted (Eloundou *et al*, 2023; Felten *et al*, 2023a). The experimental literature focuses on a handful of specific tools: ChatGPT, a chatbot generating text in response to human-provided prompts; GPT-3/GPT-4, large language models capable of generating text; and GitHub Copilot, an AI-pair-programming application.

Peng *et al* (2023) conducted a controlled experiment on professional coding, involving 95 software developers tasked with implementing an HTTP server in JavaScript. The study examined two metrics to measure performance: task completion and completion time. The availability of GitHub Copilot in the treatment group led to a 55.8% reduction in completion time compared to the control group, indicating a significant boost in software development productivity. However, there was no significant impact on task completion rates. Notably, effects were larger for both less experienced and older workers, as well as those with heavier workloads, suggesting that AI assistance can speed up programming learning curves significantly.

Similarly, Campero *et al* (2022) experimentally demonstrated a positive impact of GPT-3 on writing HTML code for both experienced programmers and non-programmers. Programmers were able to finish their work about 30 percent faster, while non-programmers reached comparable speed to human programmers who did not utilise AI tools.

Moving from writing code to writing text, Noy and Zhang (2023) conducted a controlled experiment involving 453 professionals (marketers, grant writers, data analysts, human resources workers). The participants were assigned two writing tasks for which the treatment group could use ChatGPT assistance in the second task. ChatGPT usage in the treatment group led to a 40 percent reduction in time and improved output quality by 18 percent, especially for lower-performing participants. Usage of ChatGPT also restructured task composition, with less time spent on rough-drafting and more on editing, while increasing job satisfaction and self-efficacy.

Dell'Acqua *et al* (2023) conducted a randomised controlled experiment involving 758 consultants from the Boston Consulting Group, a global management consulting firm and a selection of realistic, complex and knowledge-intensive tasks. After establishing a performance baseline for a comparable task, participants were randomly assigned to one of three conditions: no AI support, GPT-4 access, or GPT-4 AI access with a prompt engineering overview. The authors find a relationship between task type and gains from GenAI, forming a *"jagged technological frontier"*. On a product ideation task (focussing on creativity) GPT-4 support increased quality by 40 percent and speed by 25.1 percent and effects were again found to be larger for consultants in the lower-half of the skill spectrum. However, on a brand analysis task (focusing on quantitative and qualitative analysis) GPT-4 support actually reduced the likelihood to produce correct solutions.

Choi and Schwarcz (2023)'s study on GPT-4 support for students taking a law school exam confirms many of the previous findings. The authors also find stronger effects on performance for students at the bottom of the class and their study also sheds insights on the technological frontier of the usefulness of GenAI support: while GPT-4 assistance increased performance on simple multiple-choice questions, it did not have a similar impact on complex essay questions.

The above studies collectively indicate that generative AI increases speed of writing, coding and consulting, particularly benefiting inexperienced or lower-performing individuals. Some authors therefore call GenAI a 'great equaliser', but drawing such a conclusion from these studies is too simplistic.

First, these experiments focus on specific occupations, such as coders, writers, or consultants, leaving questions about the generalisability of these findings to the entire labour market. Haslberger *et al* (2023) instead use a representative sample of the British working population, covering the entire spectrum of occupational levels, skill sets and demographics. Those who were encouraged to use ChatGPT to complete three tasks (rewriting an email, assessing the strength of an argument and a reading comprehension task) showed substantial gains in speed and quality, irrespective of education, sex, or occupational background of the workers – except for older workers. The authors find that ChatGPT can reduce performance inequality *within* occupational groups, but not necessary *between* educational or occupational groups. Therefore, Haslberger *et al* (2023) find little evidence that AI reduces aggregate inequalities in productivity across various socio-economic or demographic groups.

Second, these studies only illustrate first-order effects on productivity and quality but tell us nothing about the second-order effects such as effects on employment and wages. For that, we need to look at the few studies that investigate real-world usage of GenAI, which we do in the next section.

3.2. Generative AI in real work settings

Brynjolfsson *et al* (2023) claim to be the first study to assess the impact of generative AI tools on productivity in a real-world workplace. The study focused on a large software firm's introduction of a GPT-chatbot that supports the work of its customer service agents by providing suggested (but not mandatory) responses to customer questions. The authors use data from 5,179 customer support agents. They find strong productivity effects, with a 13.8 percent increase in successfully resolved chats per hour, attributed to a reduction in average handle time (AHT), an increase in chats per hour (CPH) and a slight rise in the resolution rate (RR). All agents, regardless of skill and tenure levels, exhibited shorter handle time (AHT) and handled more chats simultaneously (CPH). However, only low-skill as well as low-tenure agents demonstrated improvement in chat resolutions (RR). The chatbot facilitated the acceleration of learning curves for new agents, capturing tacit knowledge from high-skill/high-tenure workers and integrating it into the communication of low-skill/low-tenure workers.

A recent strand of literature explores the impact of generative AI on online freelance labour markets. As freelance markets contain tasks that can be outsourced outside of organisational boundaries and require little coordination, they might be more susceptible to standardisation and automation. In this sense, these markets may act as the canary in the coal mine, showing early warning signs of future impacts on the traditional labour market. Even though it would be a stretch to think of them as representative for the entire universe of tasks and jobs, it is still useful to study this flexible and growing segment of the labour market.

Hui *et al* (2023) assessed the short-term effects of ChatGPT on employment outcomes of freelancers on Upwork. Their findings indicate that freelancers in heavily affected occupations, such as writers, faced a decrease of 2 percent in the number of monthly jobs and a decrease of 5.2 percent in monthly earnings on the platform. To ensure the reliability and validity of their results, they examine alternative specifications and conduct an additional analysis, testing the impact of a different GenAI released at a separate time (DALL-E2 and Midjourney) on another group of workers (design, image editing and art freelancers) and find similar effects. The study suggests that in the short term, generative AI decreases overall demand for various knowledge-based freelancers. Even high-quality service couldn't counteract the negative impact and top-performing freelancers were disproportionately affected.

Demirci *et al* (2023) also explored the impact of ChatGPT's introduction on the demand for freelance work in online labour markets. They categorise jobs into two types: 'automation-prone' which are more susceptible to automation and digitalisation (eg writing and statistical analysis) and 'manual-intensive' which involve more manual tasks (eg data entry and video services). The authors use a difference-in-differences model where July 2021 to November 2022 is the pre-period and December 2022 to July 2023 counts as the post-period. The study revealed a 21 percent decrease in weekly job posts within the 'automation-prone' category, indicating a shift in demand possibly influenced by ChatGPT's capabilities.

3.3. Discussion of heterogenous effects

A red thread running through a multitude of studies, both experimental (Peng *et al*, 2023; Noy and Zhang, 2023), real-work traditional (Brynjolfson *et al,* 2023) and real-work platform (Hui *et al*, 2023) is the finding of heterogenous effects across experience or skill levels. Consistently, these studies find that, within the same occupation, the less experienced or less skilled workers experience the largest gains of GenAI support. One immediate implication of these heterogenous effects is that jobs consisting mainly of writing, coding or image generation will become more accessible to a larger group of less experienced or less skilled people. At the same time, higher skilled workers (better performing writers, coders, or visual artists) might no longer be able to request better contractual conditions compared to their junior colleagues and end up in more precarious and less well-compensated jobs than they had before. Even worse, the tacit knowledge which they freely shared in examples online or in specific in-house training data, is now captured by the LLM, for which they have not been compensated. The worsening labour market conditions for some of these groups are already visible in the studies focussing on creative freelancers specialised in text or image generation, who are the first to feel the effects of reduced demand for their services.

4. Task-based vs ability-based approaches and missing perspectives

The two main bodies of literature reviewed in this paper differ in their level of analysis when it comes to GenAI exposure and impact. While the *potential* GenAI exposure in the literature is judged both at the levels of tasks (Gmyrek *et al,* 2023) and abilities (Felten *et al,* 2023a, 2023b), assessing the *actual* impact of GenAI always happens at the level of specific tasks. This makes sense when you move from the theoretic potential to the actual practice. While you can in theory compare GenAI abilities with human abilities like text comprehension or deductive reasoning, you cannot in practice go inside a firm and introduce GenAI support for all their 'deductive reasoning activities'. Instead, what you can do, is introduce GenAI support at the task level for all 'writing' or 'coding' activities within specific roles.

Both approaches – ability-based and task-based – have their merit. The ability-based approach is more concise and digestible, as there are fewer abilities than tasks to analyse. For example, the O*NET database contains 52 work-related abilities, but over 20,000 different tasks. Focussing on abilities also supports a link to the learning goals and learning content of education and training programmes. This helps programme directors to redirect their courses away from 'automatable' abilities and towards complementary abilities.

However, the task-based approach has a few clear benefits for guiding and assessing GenAI adoption in the workplace. It captures the complementarities of abilities within tasks (Weinberger, 2014) and it provides space for the emergence of new tasks or activities in response to technological change. For example, for the period between 1940-2018, Autor *et al* (2022) show that within occupations new job titles emerged in response to technological innovations that complemented the outputs of occupations while innovations that merely automated tasks slowed the emergence of such new titles. Finally, the task-based approach allows to connect two non-economic task-based perspectives: a psychological one and an organisational one. What these two perspectives have in common is their emphasis that tasks are not independent units, but in fact are parts of interdependent bundles that make up jobs and processes.

This bundle perspective on tasks is currently missing from the economic literature that considers tasks individually exposed or automatable. Almost all the reviewed empirical task-based papers, both experimental and observational, assess the productivity impact of GenAI at the level of isolated tasks, not at the level of jobs, teams or end-to-end processes. The freelancer studies are an extreme example of this, as freelancers typically operate quite independently from their client-firms, meaning that their work does not reflect traditional interdependent organisational processes.

A psychological perspective on task automation. The work design or job design literature (Parker *et al*, 2017), within industrial and organisational psychology, convincingly shows that the task content of jobs is the largest driver of worker outcomes such as engagement, commitment and stress.[8] Following the publication of one of its leading frameworks – the Job Demands-Resources model by Demerouti *et al* (2001) – job content can be defined as the balance between job demands, such as workload and pace and job resources, including autonomy and skill discretion. The engagement, commitment and health of workers that is shaped by job design in turn affects productivity, turnover and the absenteeism costs of firms (Harter *et al*, 2002, 2010; Bryson *et al*, 2017). The productivity effect found at the level of individual tasks in the economic literature might thus be enhanced or reduced by the motivational aspect of the changing task bundle, depending on how automation impacts job demands and resources.

When GenAI is used to reduce work intensity, increase workers' self-efficacy, or support their skill development, then we can expect the technology to have a positive effect on worker motivation, wellbeing and total productivity. However, if the technology takes away human autonomy, or makes jobs less conductive to learning, then we can expect a negative impact on worker outcomes (Parker and Grote, 2020). AI algorithms can even act as work designers themselves, when they take up management functions such as monitoring, scheduling and performance management (Parent-Rocheleau and Parker, 2021), which would have another second-order effect on the changing task content of jobs.[9]

An organisational perspective on task automation. The economic perspective on automation considers tasks in the labour market as independent units, some of which are exposed to GenAI and some of which are not, independently of each other. This is a simplification of reality as tasks that are grouped within organisational boundaries are typically interdependent and their execution is specific to the activities of the firm. Indeed, if they were not, these tasks would be outsourced to the market (Williamson, 1981). When two tasks are interdependent, the value generated from performing one task is different depending on the performance of the other (Puranam *et al*, 2012). Interdependence of tasks requires coordination of actions (Thompson, 1967), which is the raison d'être of organisations.

Therefore, the total productivity effect of task automation also depends on the required adaptations to the coordination mechanisms across these tasks. For example, in a data science process, the knowledge generated about a dataset in the data gathering, cleaning or exploration phase, is informative for the following phases of data modelling, interpretation and communication. Typically, the coordination across these tasks happens within a job or between people in the same team. Now, when GenAI (like OpenAI's Advanced Data Analysis) automates some early steps in the data cleaning, exploration and modelling phases, the loss of information could worsen the data scientist's ability to interpret the results and communicate recommendations in the later steps of the process. To avoid this, the GenAI should also inform the worker about relevant artifacts, patterns or anomalies in the data that should be considered when interpreting the results. In this way, the AI not only automates a task but also handles part of the coordination across the tasks shared by humans and AI systems.

Experiments on this GenAI-supported task coordination are already happening in processes where coordination happens through standardised procedures. In diagnostic medicine for example, radiologists and physicians in hospitals coordinate their work by communicating about diagnoses through standardised textual reports. While traditional AI systems had previously been tested on their ability to analyse medical images, GenAI systems can now complement them by provide textual reports with diagnostic interpretation and documentation. In a representative sample of emergency department chest radiographs, Huang *et al* (2023) found that a GenAI model produced reports of similar clinical accuracy and textual quality to radiologist reports while providing higher textual quality than teleradiologist reports.

5. Policy recommendations

The speed at which GenAI technology is developing and the promises it holds for task automation, augmentation and creation, has left most companies at loss as to what this means for the future of their jobs and industries.

[8] For a review and discussion of this literature, see Nurski and Hoffmann (2022a).
[9] For a review and discussion of the impact of AI on job quality, see Nurski and Hoffmann (2022b).

Policymakers could help guide this transition on both the side of labour demand (ie helping employers adapt their jobs and organizations) and labour supply (ie helping workers adapt their skills).

5.1. Labour demand-oriented policy

On the labour demand side, policymakers should not expect GenAI adoption to be as slow as earlier Machine Learning (ML)-based AI adoption because it is a more plug-and-play technology. Indeed, insufficient data availability and IT infrastructure is identified as one of the main barriers to ML-based AI adoption in Europe, next to skill shortages and lack of funds (Hoffman and Nurski, 2021). In contrast, GenAI is largely pre-trained, meaning it needs less training data and less modelling than ML. It also requires fewer technical skills as it has been made accessible through user-friendly interfaces like ChatGPT or Microsoft Copilot. Finally, GenAI technology is also cheaper to adopt than tailor-made ML-based AI. GenAI can thus be adopted more quickly even by organisations that are not ready for machine learning AI. Therefore, policy should focus less on stimulating adoption and more on supporting worker-friendly implementation with the following tools.

Promoting job redesign. Most companies engaging in strategic workforce planning[10] are focussing on traditional HR processes to fill future skill or labour shortages: training, recruiting and moving people across functions in the organisation (World Economic Forum, 2023). When assessing the impact of automation, naturally these companies reach for the same HR processes in their mitigating actions. They ask questions like "*should we hire more AI-building skills and fewer AI-replaceable skills?*", "*should we stop giving some trainings, like notetaking in meetings, and start giving other trainings, like prompting?*" and "*should we move people in automation-exposed functions to other functions in the organisation?*". However, what is often not in scope in these mitigating strategies, is the job design described in the previous section. Job (re)design moves the narrative away from a reactive technological determinism towards a proactive steering of a desired human-centric future. Governments can play a role in alerting companies to the existence and applicability of job redesign methods in the context of automation.

One example of such a policy initiative is Singapore's manual 'A Guide to Job Redesign in the Age of AI'[11] constructed by the Lee Kuan Yew Centre for Innovative Cities from the Singapore University of Technology and Design. This guide was commissioned by the country's Personal Data Protection Commission (PDPC) and Infocomm Media Development Authority (IMDA) under the guidance of Singapore's Advisory Council on the Ethical Use of AI and Data. The PDPC's main guiding principles for AI governance are 'explainable, transparent and fair' and 'human-centric'. This job redesign guide embodies the human-centric approach. It explains how organisations can deconstruct their jobs into tasks, assess the potential and desirability of automation, reconstruct the remaining tasks into new jobs and charting pathways from old to new jobs, all while involving and communicating with workers. The PDPC also provides implementation and self-assessment guides and a compendium of use cases.[12]

Promoting organisational agility. GenAI holds potential for both the automation and augmentation of existing tasks, as well as the creation of new tasks. Since such new activities related to AI innovations are only just arising, we cannot yet tell which demographic groups might take up these activities in the labour market. The ability to adapt to new tasks and develop new skills will be crucial not just for workers, but also for organisations. Agile organisations have the capabilities to adapt their processes as well as their workforce to rapidly developing technologies. This requires innovation capacity not just on the technological side, but also on the organisational side. Similar to promoting job redesign, policy could promote methods of organisation redesign –

[10] Proactively forecasting and planning for future workforce needs, often in the context of an ageing workforce.
[11] See the Lee Kuan Yew Centre for Innovative Cities' manual '*A Guide to Job Redesign in the Age of AI*': https://file.go.gov.sg/ai-guide-to-jobredesign.pdf
[12] See Personal Data Protection Commission Singapore website: https://www.pdpc.gov.sg/Help-and-Resources/2020/01/Model-AI-Governance-Framework

such as workplace innovation[13] – with the aim of creating more resilient and adaptable organisations with high-performance work practices (HPWPs) in Europe.

Providing SME support. Beyond creating awareness of job redesign methods and organisational agility, policymakers could provide financial support to small and medium sized enterprises (SME) to help them with worker-friendly AI adoption. Such support could consist of subsidies for training their employees or insourcing consulting advice in the above-mentioned areas. Such subsidies could be distributed through European Social Fund and should be linked to worker participation in the AI adoption process, as this can mitigate potential negative effects on workers.

5.2. Labour supply-oriented policy

Worries about jobless futures are unwarranted at this point since it is yet unclear how the balance between automation and augmentation will play out[14]. At the same time, some groups of workers will undoubtedly be heavily impacted, as the labour market might see a substantial reallocation of labour. Policy could play a role in supporting these workers through the transition.

Providing GenAI literacy training. Throughout this paper, a wide variety of occupations have been identified as strongly exposed to GenAI, such as finance professionals, legal professionals, teachers, or general clerks. Therefore, programme directors in educational institutions would do well to integrate GenAI in their curricula across the board. Employers could provide firm-specific training, while policymakers could offer more general GenAI literacy trainings to the entire population. This could be done in a similar way as the Finnish Massive Open Online Course (MOOC) 'Elements of AI' which focuses on earlier generations of ML-based AI. The course was originally developed by the Finnish Center for Artificial Intelligence (FCAI) but has since been translated into all EU languages with the help of the European Commission[15]. While this previous course focused on Machine Learning, a new initiative could focus on responsibly using GenAI applications like ChatGPT and Midjourney. Such a course should pay extra attention to teaching critical thinking which will be imperative in judging and verifying GenAI output.

Improving social dialogue and social safety nets. Worker involvement in technology design, adoption and implementation can mitigate potential negative impact of GenAI adoption on jobs and workers. Unions should therefore acquire the necessary knowledge and skills to be part of the GenAI conversation. Emphasis should be placed on fostering social dialogue, a crucial tool for ensuring responsible AI adoption, comprehensive social protection and skills development programmes that effectively counteract the negative impacts of automation. This approach ensures a well-organised process that considers the interests of workers, employers and society at large. Furthermore, social safety nets should be put in place to provide a cushion for those affected by technological disruption of the labour market. This may include unemployment benefits, healthcare coverage and other support mechanisms to ease the transition.

5.3. Research and regulation policies

Financing further research on the jagged frontier. As demonstrated by Dell'Acqua *et al* (2023), further research should be undertaken to gain a deeper understanding of the technological frontier. The study reveals variations in the effectiveness of AI across professional workflows, identifying tasks within and outside the technological frontier. Tasks within the frontier showcase a substantial boost in worker productivity when AI is applied, while tasks outside the frontier saw decreased effectiveness with GenAI support. Hence, it is suggested that both companies and governments invest effort in identifying tasks situated within this frontier. The results of this research should feed back into the GenAI literacy training mentioned above, so that workers can use GenAI support for the right selection of tasks.

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[13] https://single-market-economy.ec.europa.eu/industry/strategy/innovation/workplace-innovation_en

[14] A 2021 study by the OECD found no support for net job destruction in jobs at risk of automation 10 years earlier, even though these occupations did experience slower employment growth (Georgieff and Milanez, 2021).

[15] See Elements of AI website: https://www.elementsofai.com/eu2019fi

Setting up monitoring and reporting. Given the speed of technological innovation, policymakers should track its impact on vulnerable groups in the labour market closely. A data-driven approach could inform policymakers and inspire policy adjustments to address emerging issues. We recommend establishing a systematic framework for gathering and analysing data related to GenAI adoption as well as robust mechanisms for monitoring and reporting on the labour market impact of GenAI across different demographic groups. AI occupational exposure scores should be updated regularly to follow the speed of AI development itself. Regular analysis of the demographic composition of affected workers will help identify patterns and trends, particularly focusing on gender disparities in the impact of AI on employment, wages and career trajectories.

Assessing ethical AI guidelines. Ethical guidelines on the use of GenAI at work are necessary to ensure that the benefits of these technologies extend to all members of society in an inclusive way. Special emphasis should be placed on addressing and minimising gender and racial biases in GenAI algorithms. The High-Level Expert Group on AI which is set up by the European Commission has developed the 'Ethics Guidelines for Trustworthy AI'[16] and a similar initiative has been set up by UNESCO[17]. Both initiatives took place before the advent of GenAI, in the context of more traditional machine learning AI. These guidelines could be reassessed given the recent developments to make sure they are still fit for purpose in this new wave of AI.

[16] See the High-Level Expert Group on AI's guideline: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[17] See the UNESCO guidelines: https://www.unesco.org/en/artificial-intelligence/recommendation-ethics

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Appendix A: Additional Descriptive Evidence from 2021

Table A1. Country exposure to generative AI

Country	AI_exposure	LM_exposure	IG_exposure	ILO_exposure
LU	0.44	0.47	0.29	0.36
NL	0.32	0.35	0.17	0.34
SE	0.29	0.31	0.2	0.33
BE	0.2	0.25	0.05	0.34
IE	0.19	0.22	0.07	0.34
DK	0.18	0.21	0.04	0.33
DE	0.17	0.21	0.04	0.34
FR	0.14	0.18	0.03	0.32
AT	0.11	0.14	-0.002	0.33
FI	0.11	0.14	0.01	0.31
EE	0.09	0.1	0.05	0.32
CY	0.09	0.14	-0.07	0.33
LT	0.09	0.1	0.04	0.3
PT	0.07	0.1	-0.04	0.32
LV	0.05	0.06	-0.01	0.3
PL	0.04	0.04	0.01	0.31
EL	0.03	0.06	-0.11	0.32
ES	0.01	0.07	-0.14	0.31
CZ	0.01	0.01	-0.02	0.31
IT	0.01	0.05	-0.12	0.32
SK	0	0.01	-0.06	0.31
HU	-0.01	0.003	-0.05	0.31
HR	-0.03	-0.01	-0.11	0.31
RO	-0.19	-0.19	-0.19	0.28

Table A2. Percentage of male and female workers in each age group

Age groups	Percentage of male workers	Percentage of female workers
Y15-19	54.26	45.74
Y20-24	54.2	45.8
Y25-29	53.68	46.32
Y30-34	54.21	45.79
Y35-39	53.91	46.09
Y40-44	52.99	47.01
Y45-49	52.84	47.16
Y50-54	52.57	47.43
Y55-59	53.04	46.96
Y60-64	55	45
Y65_	61.67	38.33

Table A3. Top and bottom ISCO 2008 occupations at the three-digit level by generative AI measures

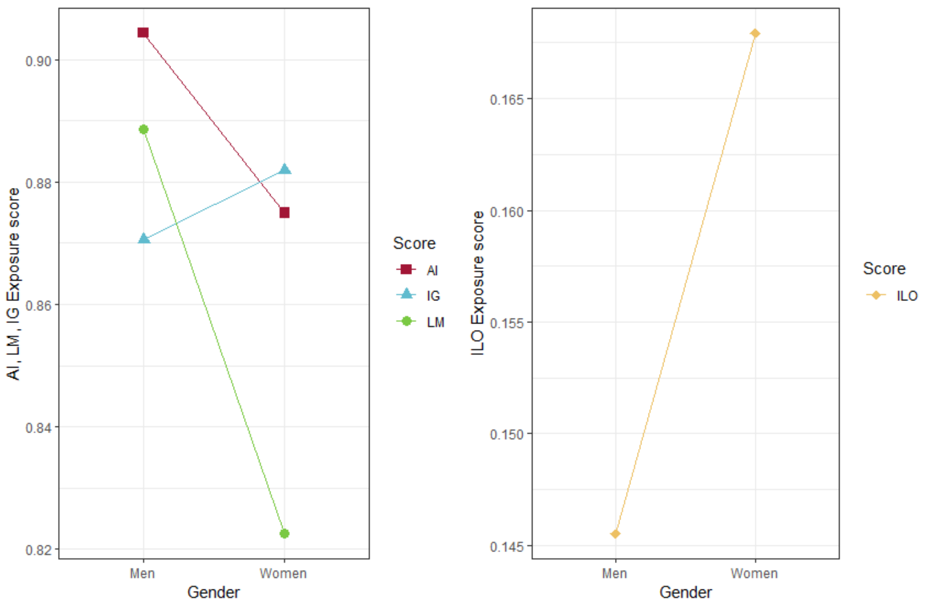
Top 15 occupations exposed to AI	**Top 15 occupations exposed to LM**	**Top 15 occupations exposed to IG**	**Top 15 occupations exposed to ILO**
212 Mathematicians, actuaries and statisticians	261 Legal professionals	214 Engineering professionals (excluding electrotechnology)	413 Keyboard operators
241 Finance professionals	231 University and higher education teachers	216 Architects, planners, surveyors and designers	411 General office clerks
261 Legal professionals	952 Street vendors (excluding food)	251 Software and application developers and analysts	422 Client information workers
263 Social and religious professionals	263 Social and religious professionals	212 Mathematicians, actuaries and statisticians	431 Numerical clerks
231 University and higher education teachers	241 Finance professionals	252 Database and network professionals	412 Secretaries (general)
431 Numerical clerks	264 Authors, journalists and linguist	211 Physical and earth science professionals	264 Authors, journalists and linguist
411 General office clerks	412 Secretaries (general)	122 Sales, marketing and development managers	441 Other clerical support workers
122 Sales, marketing and development managers	411 General office clerks	215 Electrotechnology engineers	421 Tellers, money collectors and related clerks
242 Administration professionals	233 Secondary education teachers	133 Information and communication technology service managers	334 Administrative and specialized secretaries
251 Software and application developers and analysts	243 Sales, marketing and public relations professionals	241 Finance professionals	262 Librarians, archivist and curators
332 Sales and purchasing agents and brokers	242 Administration professionals	262 Librarians, archivists and curators	332 Sales and purchasing agents and brokers
233 Secondary education teachers	212 Mathematicians, actuaries and statisticians	132 Manufacturing, mining, construction, and distribution managers	241 Finance professionals
214 Engineering professionals (excluding electrotechnology)	332 Sales and purchasing agents and brokers	242 Administration professionals	331 Financial and mathematical associate professionals
243 Sales, marketing and public relations professionals	122 Sales, marketing and development managers	111 Legislators and senior officials	212 Mathematicians, actuaries and statisticians
121 Business services and administration managers	422 Client information workers	264 Authors, journalists and linguist	432 Material-recording and transport clerks

Bottom 5 occupations exposed to AI	**Bottom 5 occupations exposed to LM**	**Bottom 5 occupations exposed to IG**	**Bottom 5 occupations exposed to ILO**
631 Subsistence crop farmers	931 Mining and construction labourers	911 Domestic, hotel and office cleaners and helpers	941 Food preparation assistants
912 Vehicle, window, laundry and other hand cleaning workers	713 Painters, building structure cleaners and related trades workers	932 Manufacturing labourers	634 Subsistence fishers, hunters, trappers and gaterers
931 Mining and construction labourers	634 Subsistence fishers, hunters, trappers and gaterers	941 Food preparation assistants	921 Agricultural, forestry and fishery labourers
911 Domestic, hotel and office cleaners and helpers	912 Vehicle, window, laundry and other hand cleaning workers	631 Subsistence crop farmers	912 Vehicle, window, laundry and other hand cleaning workers
713 Painters, building structure cleaners and related trades workers	631 Subsistence crop farmers	912 Vehicle, window, laundry and other hand cleaning workers	632 Subsistence livestock farmers

Table A4. Top five ISCO 2008 occupations at two-digit level by generative AI measures

Top 5 occupations exposed to AI	**Top 5 occupations exposed to LM**	**Top 5 occupations exposed to IG**	**Top 5 occupations exposed to ILO**
24 Business and Administration Professionals	95 Street and Related Sales and Service Workers	25 Information and Communications Technology Professionals	41 General and Keyboard Clerks
12 Administrative and Commercial Managers	24 Business and Administration Professionals	21 Science and Engineering Professionals	42 Customer Services Clerks
41 General and Keyboard Clerks	41 General and Keyboard Clerks	12 Administrative and Commercial Managers	44 Other Clerical Support Workers
25 Information and Communications Technology Professionals	26 Legal, Social and Cultural Professionals	24 Business and Administration Professionals	43 Numerical and Material Recording Clerks
26 Legal, Social and Cultural Professionals	12 Administrative and Commercial Managers	35 Information and Communications Technicians	33 Business and Administration Associate Professionals

Figure A1. Generative AI exposure to gender in standard deviation



Appendix B: Additional Descriptive Evidence between 2016-2022

Table B1: Employment shares and their changes by level of highest educational attainment

Highest educational attainment	2016	2022	Change
ISCED 1	3.18	2.79	-0.39
ISCED 2	14.60	13.64	-0.96
ISCED 3	44.79	41.39	-3.41
ISCED 4	4.37	4.53	0.16
ISCED 5	5.03	4.99	-0.04
ISCED 6	11.93	14.39	2.46
ISCED 7	14.68	16.62	1.94
ISCED 8	0.97	1.24	0.28
NA	0.45	0.41	-0.05

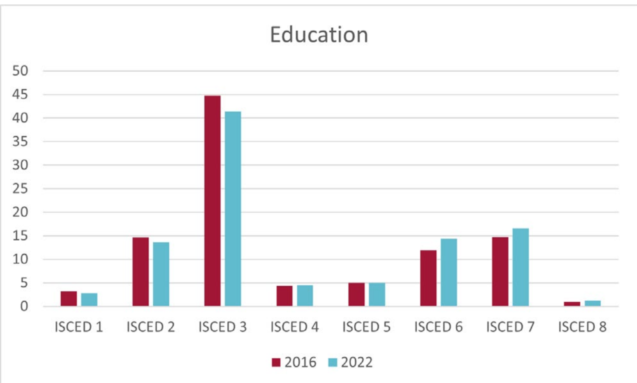
Notes: Employment shares are shown as percentages, changes are percentage points.

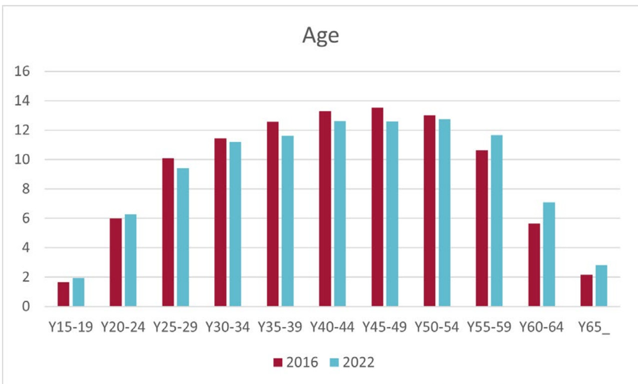
Table B2: Employment shares and their changes by age group

Age groups	2016	2022	Change
Y15-19	1.65	1.94	0.29
Y20-24	5.98	6.28	0.30
Y25-29	10.09	9.42	-0.68
Y30-34	11.43	11.20	-0.23
Y35-39	12.56	11.61	-0.95
Y40-44	13.29	12.62	-0.68
Y45-49	13.52	12.60	-0.92
Y50-54	13.01	12.74	-0.28
Y55-59	10.65	11.67	1.02
Y60-64	5.65	7.11	1.46
Y65_	2.15	2.81	0.67

Notes: Employment shares are shown as percentages, changes are percentage points.

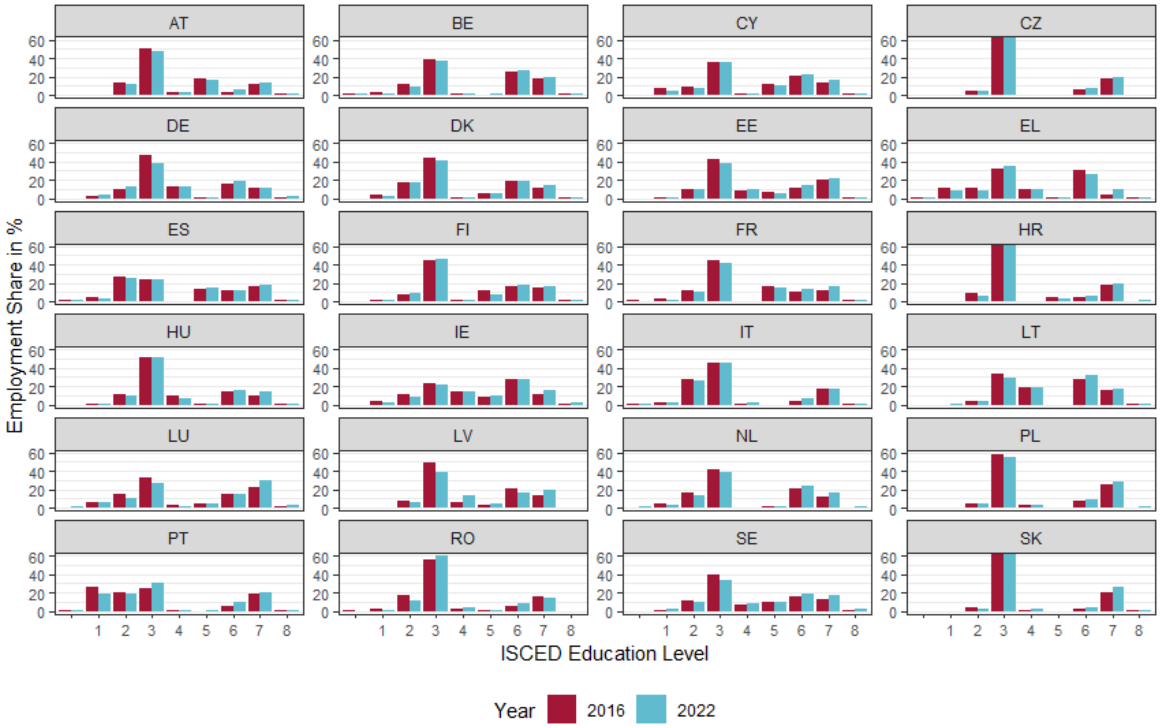
Figure B1: Employment shares by worker demographics





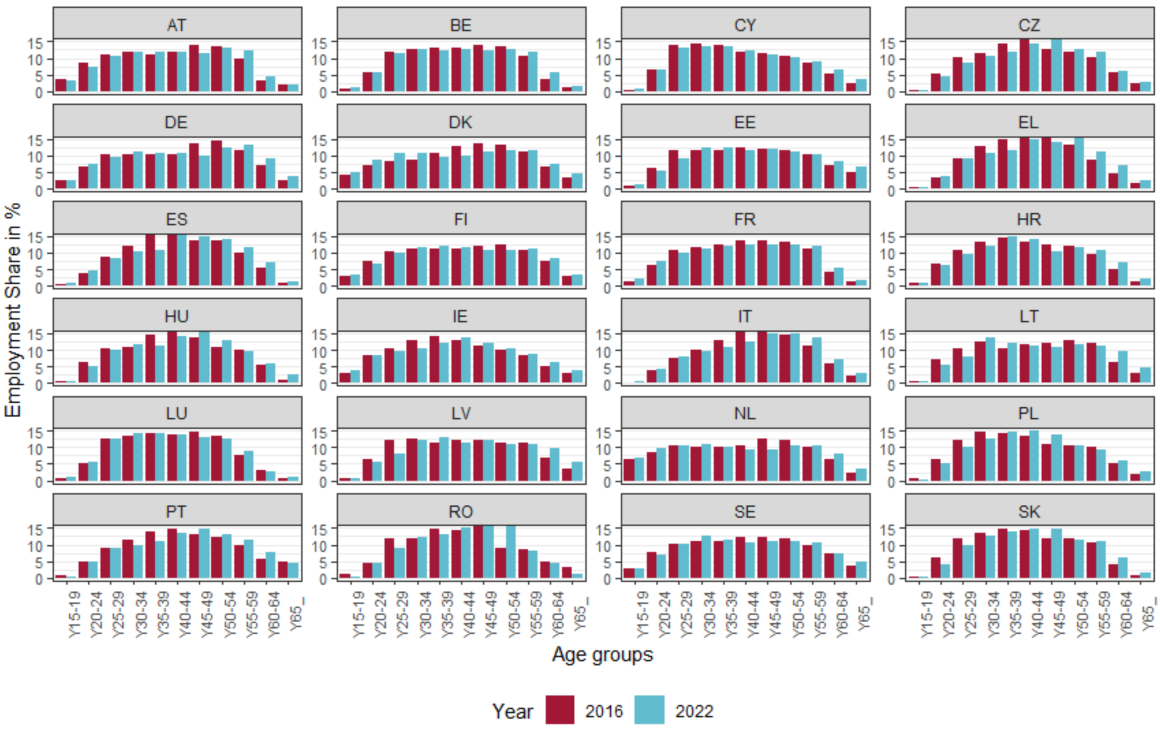
Notes: Y-axis indicates average annual employment shares.

Figure B2: Employment shares by education across countries



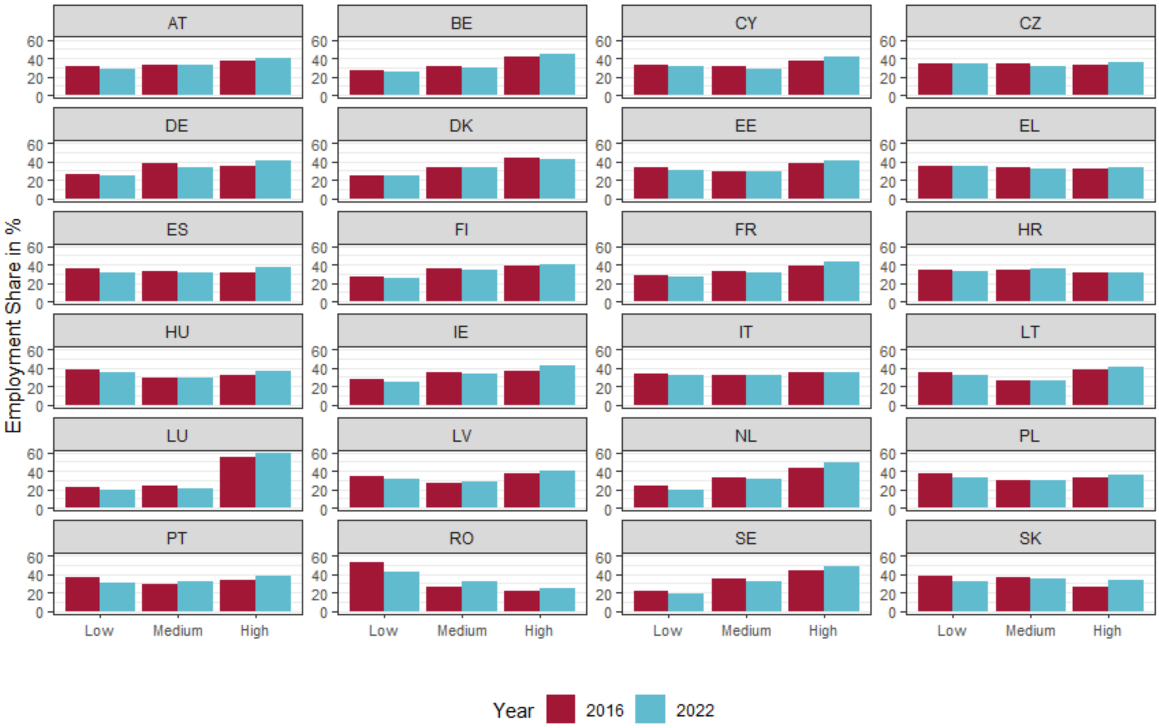
Notes: Y-axis indicates average annual employment shares.

Figure B3: Employment shares by age groups across countries



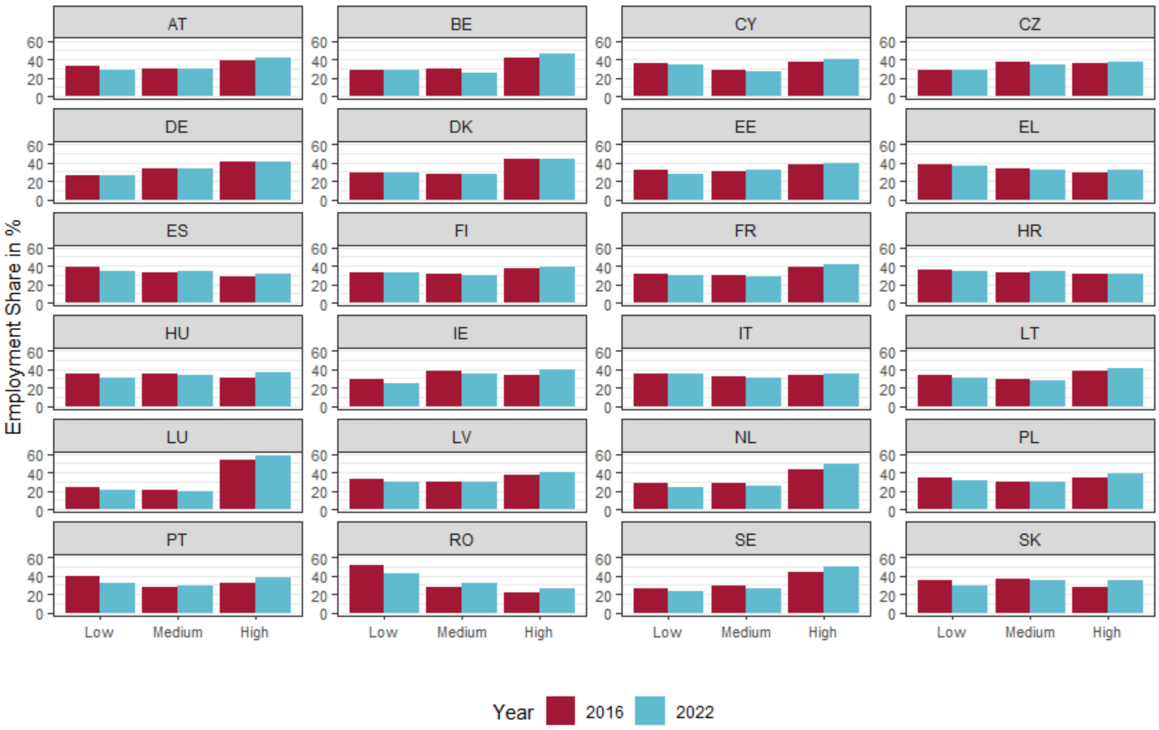
Notes: Y-axis indicates average annual employment shares.

Figure B4: Employment shares by AI (Felten) across countries



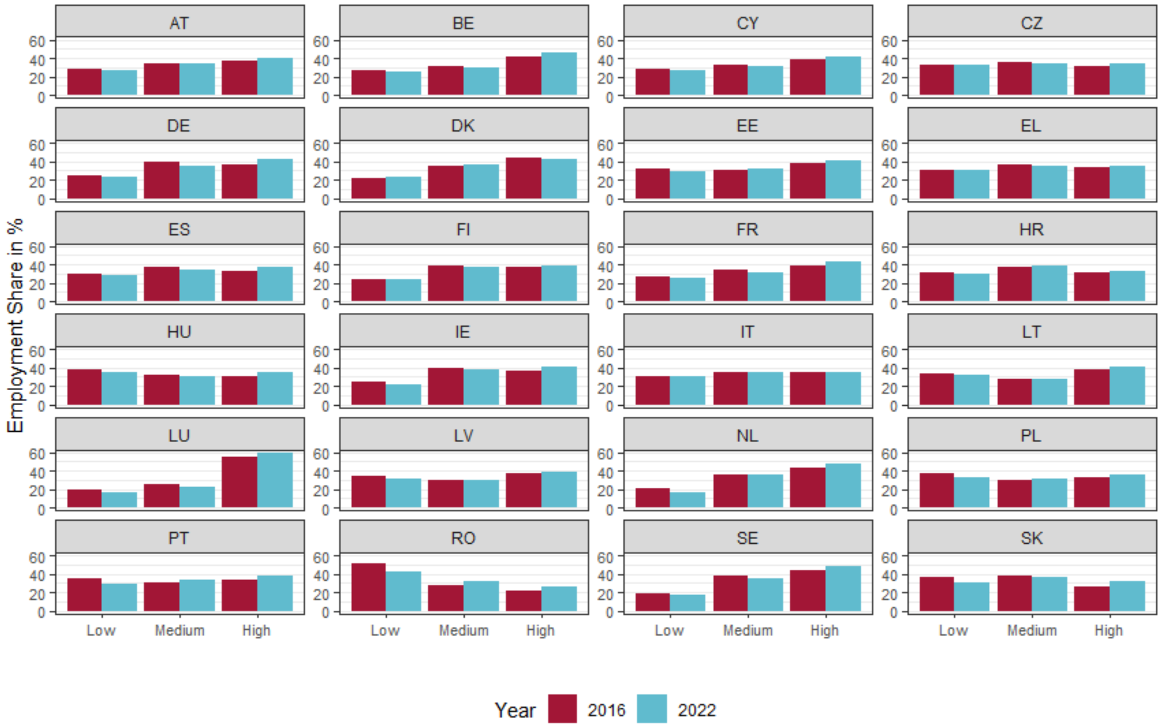
Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores.

Figure B5: Employment shares by IG (Felten) across countries



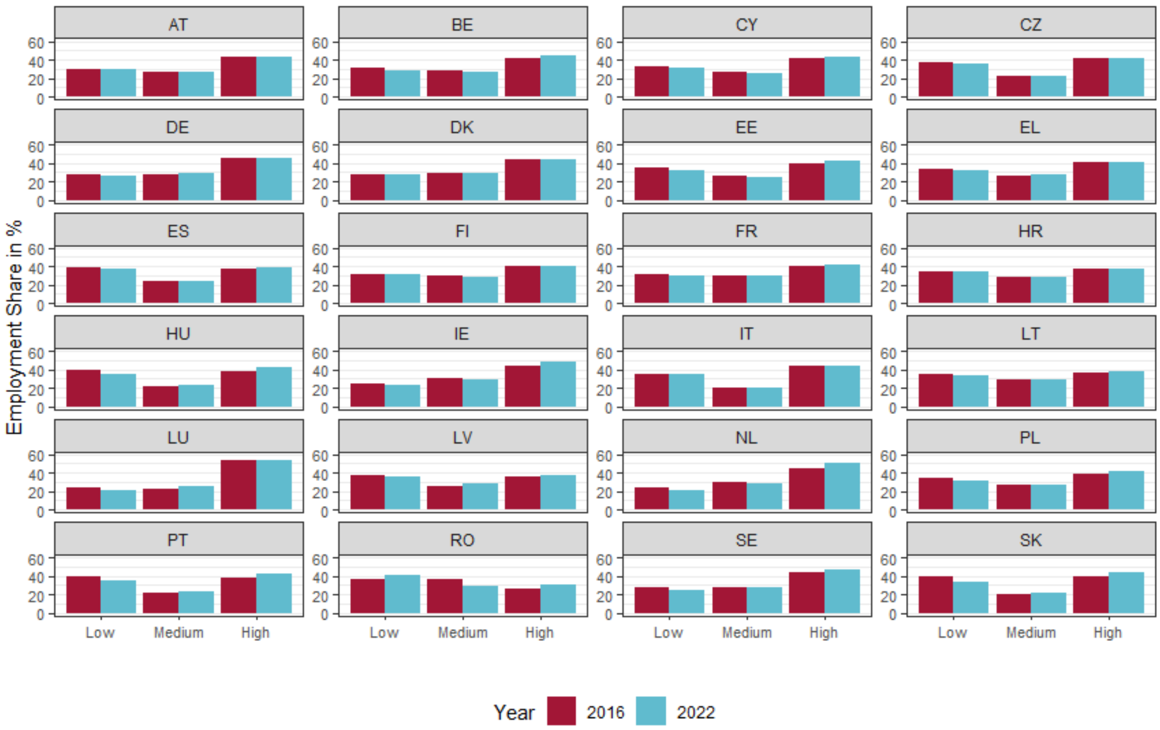
Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores.

Figure B6: Employment shares by LM (Felten) across countries



Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores.

Figure B7: Employment shares by ILO across countries



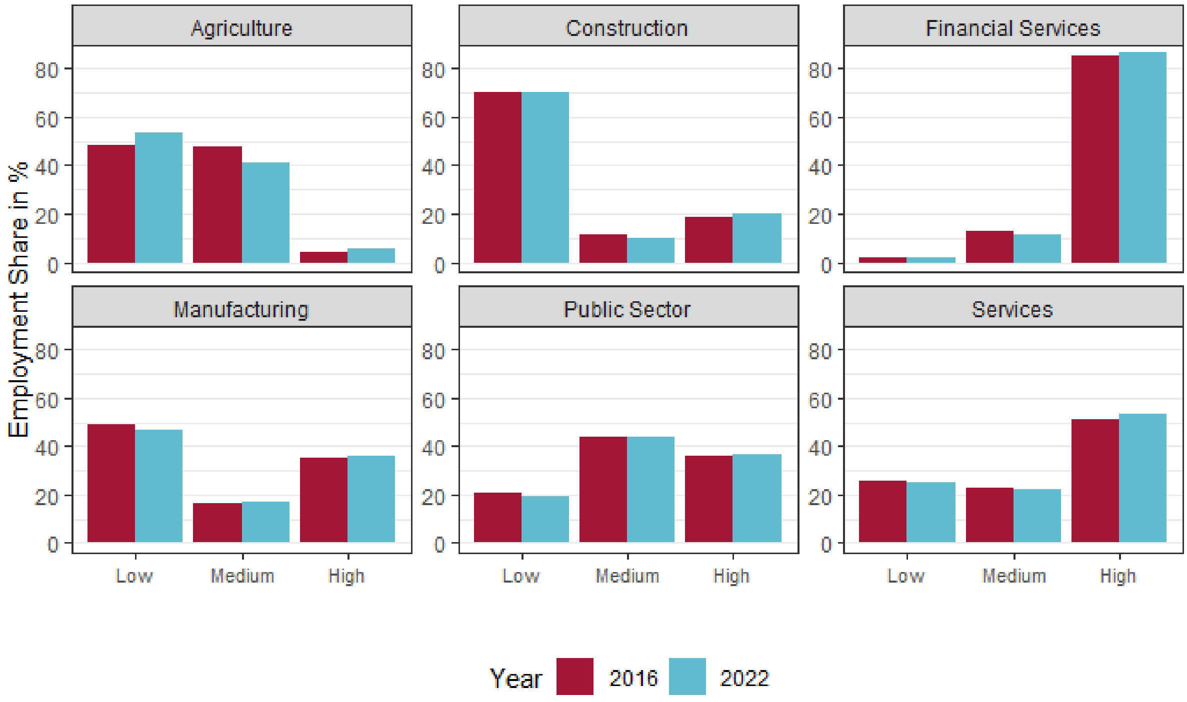
Notes: Y-axis indicates average annual employment shares. Technology measure categories (low, medium, high) reflect terciles of the respective technology measure's scores.

Figure B9: Employment shares by AI across sector

Figure B10: Employment shares by IG across sector

Figure B11: Employment shares by LM across sector

Figure B12: Employment shares by ILO across sector



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