Employment and work aspects of technological advancements

Strategic foresight – *driver 1*

EUROPEAN LABOUR AUTHORITY

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Table of Contents

Definition........5
Developments to date........5
Future perspectives........10
Hypotheses about the future........14
H1: Automation follows its existing trajectory........14
H2: The diffusion of AI increases........14
H3: Increasing platformisation of work and employment........14
References........16

List of Tables

Table 1: Probability of automation and impact on employment by level of analysis – review by Filippi et al. (2023)........12

List of Figures

Figure 1: Digitalisation intensity of establishments by sector, EU27 and the UK, 2019 (%)........6

Figure 2: Percentage of affirmative answers to the question 'As a result of the new computer programmes or software you learnt for your main job in the last 12 months, did your job tasks change in any of the following ways? You now do some different tasks', by sector........8

Figure 3: Percentage of affirmative answers to the question 'To what extent do you think new digital or computer technologies in your company or organisation can or will do part or all of your main job?', by sector........9

Definition

Contemporary labour markets are characterised by the impact of technological advancements. This is widely referred to as 'digitalisation'. Digitalisation means the broad transformation brought about by the widespread adoption of digital technologies. Three broad categories of combined applications of digital technologies are differentiated: automation, digitisation and coordination by platforms[1].

Automation is understood as the replacement of human activities by technology. Digitisation captures the use of sensors and rendering devices to translate the physical production process, or parts of it, into digital information (and vice versa)[2]. Coordination by platforms refers to entities that organise digital networks to coordinate transactions in an algorithmic way[3].

These three pillars are supplemented by artificial intelligence (A), a general-purpose technology that enables and supports the application of many other technologies[4]. Public discussions tend to define AI as GPTs (generative pre-trained transformers) which, apparently, have the capacity to mimic activities previously thought to be the preserve of humans (for instance, undertaking literature reviews of a type provided here)[5]. In reality, however, AI encompasses more than GPTs. In general, it refers to the capacity of machines to engage in reasoning and problem-solving.

To date, the evidence suggests that technological change impacts the labour market as regards both, employment aspects (e.g. types of contracts, employment status) as well as working conditions (e.g. working time, place of work, work organisation). Different types of technology are found to have different effects on work and employment, workers and employers, sectors and occupations.

Developments to date

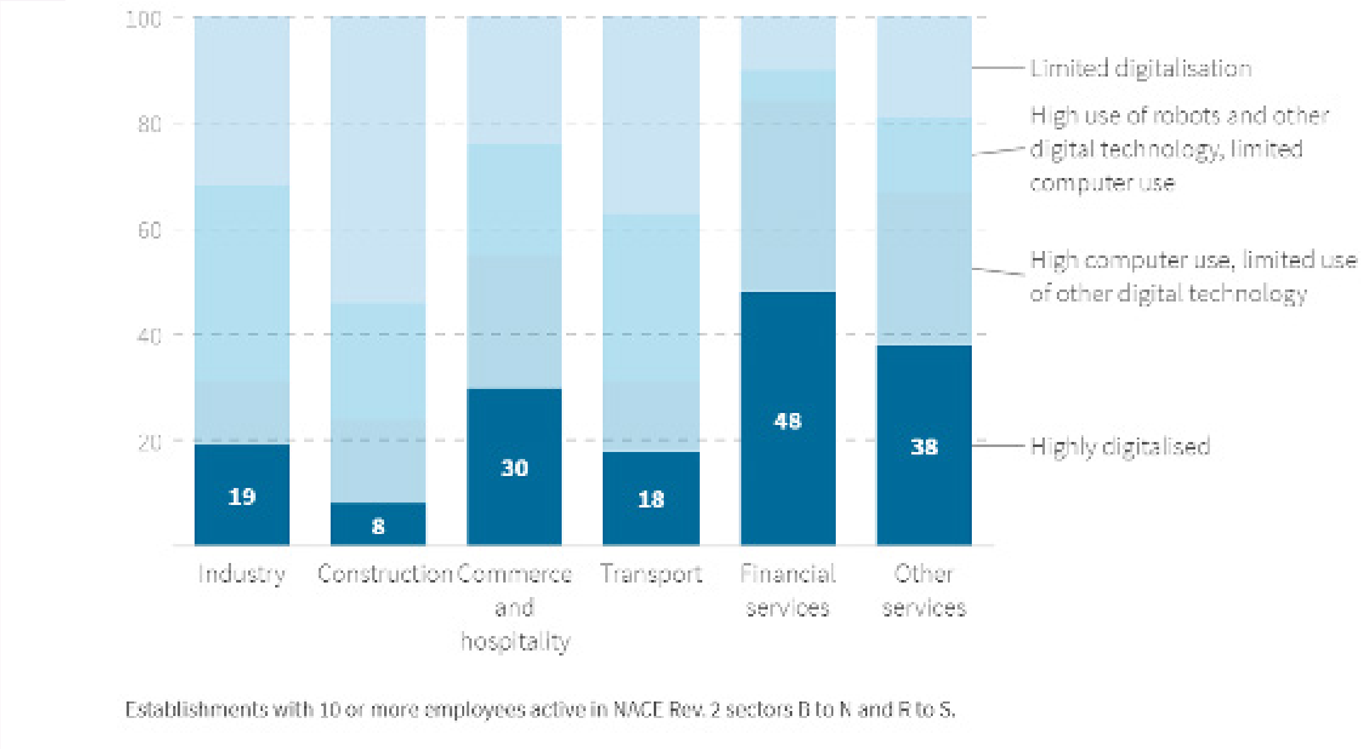
Technology is one of the main drivers of change affecting the demand for, and quality, of labour. It has the capacity to both create and destroy jobs, sometimes rapidly over a short period of time and change their task content. This has been evident from the Industrial Revolution onwards. In general, technological change is seen to be both employment and skill enhancing. It has tended to create more jobs than it destroys (Filippi et al., 2023).

Technological change can create a virtuous circle which simultaneously creates new jobs, brings about productivity and competitiveness gains from the introduction of new production processes alongside the creation of new good and services, and thereby stimulates economic growth (Vivarelli, 2014; Calvino and Virgillito, 2018). R&D expenditure can be used as a proxy measure of technological change. Several studies indicate the way in which, at the firm level, relatively high levels of R&D expenditure are associated with employment growth and skills development. Examples of studies which demonstrate this effect include those of start-up firms in the Netherlands (Stam and Wennberg, 2009); US high-tech manufacturing firms (Coad and Rao, 2011); publicly traded European firms (Bogliacino et al., 2014); and Spanish manufacturing firms operating in developing countries (Pellegrino et al., 2019). The positive impact on employment is mostly found in high-tech enterprises and / or large firms.

Similar findings are shown by the European Company Survey 2019. It finds a positive relationship between the digitalisation intensity of establishments and indicators like employment growth and workplace well-being. From a sectoral perspective, however, digitalisation intensity differs substantially. Sectors strongly affected by current labour shortages, such as construction or transport, show the lowest share of highly digitalised establishments[6].

1 Definitions | European Foundation for the Improvement of Living and Working Conditions (europa.eu)
2 Definitions | European Foundation for the Improvement of Living and Working Conditions (europa.eu)
3 Definitions | European Foundation for the Improvement of Living and Working Conditions (europa.eu)
4 Definitions | European Foundation for the Improvement of Living and Working Conditions (europa.eu)
5 To confirm, this has been written by a human.
6 Automation, digitisation and platforms in the world of work | European Foundation for the Improvement of Living and Working Conditions (europa.eu) and Employment impact of digitalisation | European Foundation for the Improvement of Living and Working Conditions (europa.eu)

Figure 1: Digitalisation intensity of establishments by sector, EU27 and the UK, 2019 (%)



Source: ECS2019 management questionnaire

The impact of technological change in practice is seen to have a differential impact by occupation. Enhanced labour market opportunities are generally observed for engineering profiles, data scientists and managerial roles with multidisciplinary skills[1], hinting towards increasing labour shortages in occupations based on science, technology, engineering and mathematics (STEM) qualifications and workers with a multidisciplinary skill set.

The theory of skills-biased technological change (SBTC) posits that technological change increases the demand for highly-skilled and educated workers and provides a substitute for the work of relatively low-skilled and educated ones. This theory explained how, over time, technological progress increased the demand for relatively highly skilled workers (Goldin and Katz, 1998). It resulted in an increased wage and employment gap between workers by skill and education (Katz and Murphy, 1992; Autor et al., 2003; Acemoglu and Autor, 2011). Katz (2000) observed that the computerisation of certain tasks in the 1980s accelerated the already growing demand for more skilled/educated workers and further increased the rise in their real earnings and exacerbated income inequality in the US. It was noted that the employment of more skilled workers was strongly positively correlated with capital intensity and the introduction of new technologies (i.e., evidence of a capital-skill complementarity) (Levy and Murnane, 1996).

The theory of SBTC could not explain observed patterns of change in the labour market which saw a fall in employment in the middle of the occupational hierarchy and growth in relatively high and low skilled work. This was explained in part with reference to the types of tasks people undertake in their jobs. Autor et al. (2003) proposed a new theoretical explanation to account for the observed shifts in occupational employment: the theory of routine-based technological change (RBTC). This shifted the focus to the task content of jobs (Sebastian and Biagi, 2018). The evidence revealed that the tasks undertaken in some jobs were routine in the sense that they were repetitive and therefore predictable even though they may be relatively complex tasks that required workers to be relatively highly skilled in order to execute them. The long-term decrease in computer prices encouraged labour-intensive industries that relied upon labour to perform routine tasks to invest in the computerised technologies that allowed these tasks to be automated (Acemoglu and Autor, 2011; Autor et al., 2002; Bresnahan et al., 2002; and Bartel et al., 2007).

Unlike jobs in the middle of the occupational hierarchy, relatively high-skilled and relatively low-skilled jobs require a mix of skills which are not predictable to the same degree and therefore less susceptible to automation. Both require the application of both cognitive and non-cognitive skills of one kind or another (Autor et al., 2003;

1 Employment impact of digitalisation | European Foundation for the Improvement of Living and Working Conditions (europa.eu)

Deming, 2017). An increase was observed among occupations making intensive use of non-routine cognitive tasks between 1960 and 1998 (Autor et al., 2002). In line with this, Deming and Noray (2019) found that the skill content of jobs changed significantly between 2007 and 2017. Skill requirements increased across all occupations in the US labour market, alongside ones linked to, for example, coordination, negotiation, persuasion, and social perceptiveness. There was also an increase in the demand for people with skills linked to AI.

According to the theory of RBTC, the effect of technological progress is the replacement of 'routine' labour which tends to be clerical and skilled trades / assembler jobs in the middle of the wage distribution resulting in the hollowing out of the occupational structure of employment or (the wage) polarisation in the demand for labour (Autor et al., 2006; Goos and Manning, 2007). There are, it should be noted, dissenting views about whether technological change is the cause of any polarisation or whether there is actually any definitive evidence that polarisation has or is taking place (Fernández-Macías and Hurley, 2017; Bessen, 2016; Eurofound, 2014). Additionally, Haslberger (2021) investigates a paradox in occupational polarisation, highlighting how technological changes, though routine and skill-biased, may result in occupational upgrading rather than the anticipated polarisation, influenced by variations in occupational routine-wage hierarchies across countries. Nevertheless, employment polarisation (or the hollowing out of the occupational structure of employment), although not strictly driven by digitalisation was evident in a few EU countries (France, the Netherlands, Germany, Slovakia, and the UK) between 1995 and 2008. The financial crisis may have introduced a degree of polarisation across Europe as a whole, but this dissipated after 2011 when changes in the wage or skill structure of employment resumed its pre-financial crisis trend. In other words, the evidence revealed growth in relatively well-paid jobs.

Rather than solely concentrating on the creation and destruction of jobs the focus has now shifted to how tasks within existing jobs change in relation to technological change. There are concerns that with new technological developments, such as AI, the automation of cognitive non-routine tasks becomes possible (Brynjolfsson and McAfee, 2011). This trend potentially poses a threat to a much wider range of jobs than hitherto. Evidence from the EU, based on the Cedefop European Skills and Jobs Survey, suggests that new technology threatens around 8-14% of employment. These jobs are typically low-skilled ones whose incumbents have relatively little access to training (Pouliakas, 2008). Additionally, McGuiness et al. (2021) show that 16% of EU workers experienced technological change that could lead to skills obsolescence.

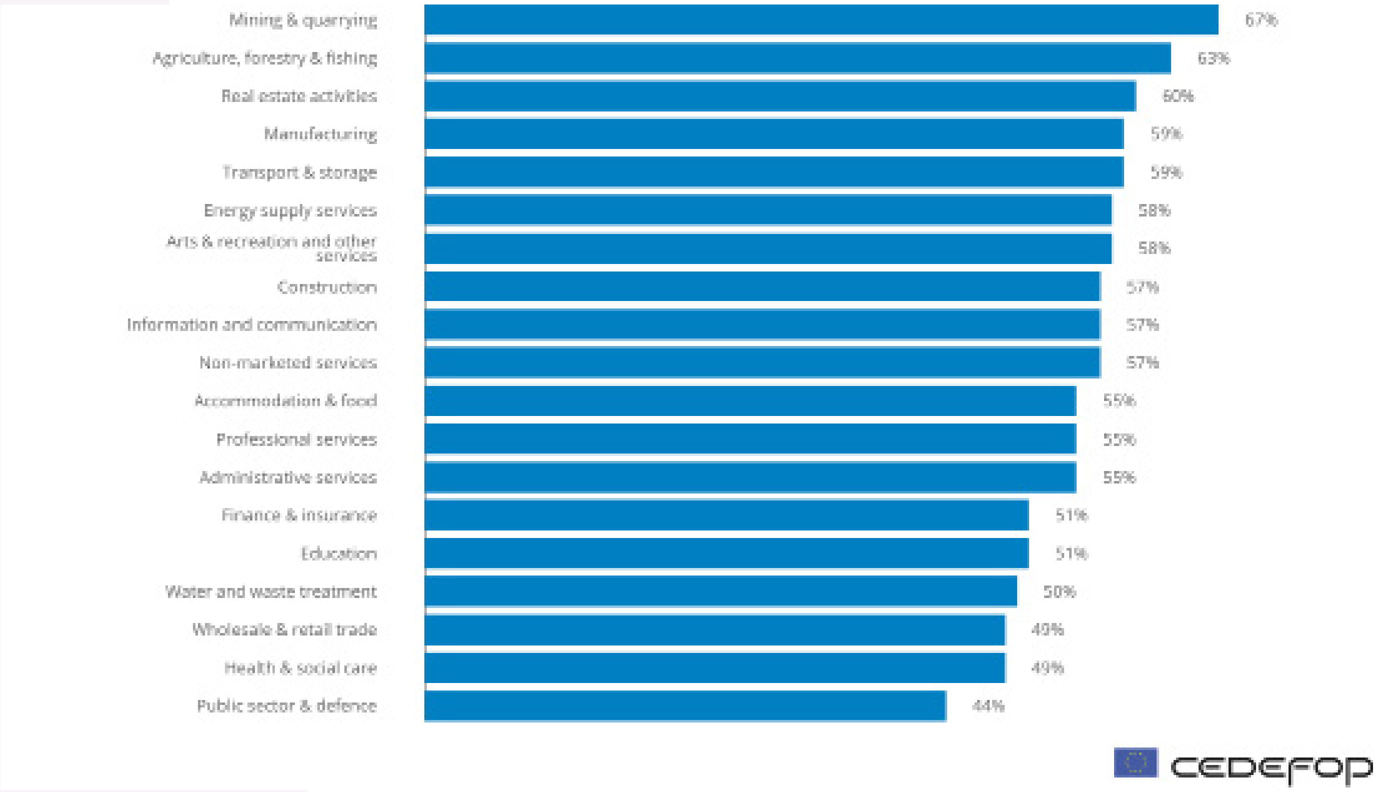
It could also be the case that certain groups of workers are more affected by technological change than others. Older workers (however defined) who initially acquired economically valuable skills, may see their expertise being rapidly supplanted by new technologies and associated new ways of working (i.e., they are subject to skills obsolescence). While certain technical skills may become less relevant with technological advancements, it is essential to note that with age and tenure in the labour market, older workers often possess non-technical skills such as social competencies and decision-making abilities that are not easily replaceable by technology. Notably, research on German firms, as demonstrated by Dauth et al. (2017), indicates that the impact of robots is mostly neutral for incumbent, older workers, while younger entrants bear the brunt of technological changes.

Research conducted by Cedefop (2020) challenges the idea that automation will lead to widespread job loss, suggesting that while automation is advancing, a jobless future is unlikely, questioning some of the more dramatic warnings of future large-scale job loss (see below for details). This is because workers can adjust to technological change by obtaining the skills required by the market (Arntz et al., 2016). Second, the high price of capital, political activism, regulatory concerns, and ethical aspects can slow the pace of technological change leaving time for labour markets to adapt (Frey and Osborne, 2017). Cortes et al. (2017) reveal that the primary factor contributing to the decrease of employment in jobs susceptible to automation is a reduction in the number of new hires to them rather than the enforced exit of existing workers.

The problem may be less that of employment displacement as one of a mismatch between the demand for and the supply of labour. Despite significant investments in skills anticipation, education, and training, a substantial number of workers in the EU report that their skills are mismatched to their work. Simultaneously, surveys indicate that employers face challenges in finding workers with the right skills. In 2020/2021, four out of 10 workers said that their level of educational attainment was mismatched to their current job: of these, 28% said they were overqualified, and 12% that they were underqualified (Cedefop, 2022). Seven out of 10 skilled workers identified significant gaps between the skills they possessed and the skills they needed in their day-to-day jobs. Digital skills is one area where workers report being underskilled, with 52% of adult workers reporting that they needed to acquire new digital skills to do their job at a more proficient level; of these, only one in four received specific training in digital skills in 2020/2021 (Cedefop, 2022).

Evidence from the second European Skills and Jobs Survey (ESJS2), conducted in 2021, provides detailed information on the actual changes workers have experienced in their jobs over the recent past. As such it provides empirical data on the extent to which new technology, especially new computer software and computerised machinery, has affected people's employment. It reports that 4% of the EU+ workforce (EU27 plus Norway and Iceland) only saw some of their job tasks being replaced by new digital technology without taking on different or new tasks. 22% experienced both task generation and destruction, while 9% only started doing new or different tasks. However, 45% of the EU+ workforce believe that they need or will need new knowledge and skills because of the new digital technologies in their workplace (Cedefop, 2022). The ESJS2 reveals the sectors where automation is taking root. Workers in manufacturing, agriculture, forestry and fishing, energy supply, construction, and mining and quarrying were the most likely to report working with robots as part of their main job in the preceding month. As some of these sectors are strongly affected by labour shortages (e.g. construction, some manufacturing occupations), automation might positively contribute to solving labour market imbalances. When respondents were asked if they now performed different or new tasks as a result of the introduction of new computer programmes or software/new computerised machinery in the last 12 months, certain sectors consistently emerged with high positive response rates (see Figure 1). These sectors included, in order: mining and quarrying (67% of respondents reporting new tasks), agriculture forestry and fishing (63%), real estate activities (60%), manufacturing (59%), and transport and storage (59%) (Cedefop, 2022). Such developments hint towards potential skill shortages emerging in the short run, as capacities of the incumbent workforce might need adaptation to the new task requirements.

Figure 2: Percentage of affirmative answers to the question 'As a result of the new computer programmes or software you learnt for your main job in the last 12 months, did your job tasks change in any of the following ways? You now do some different tasks', by sector

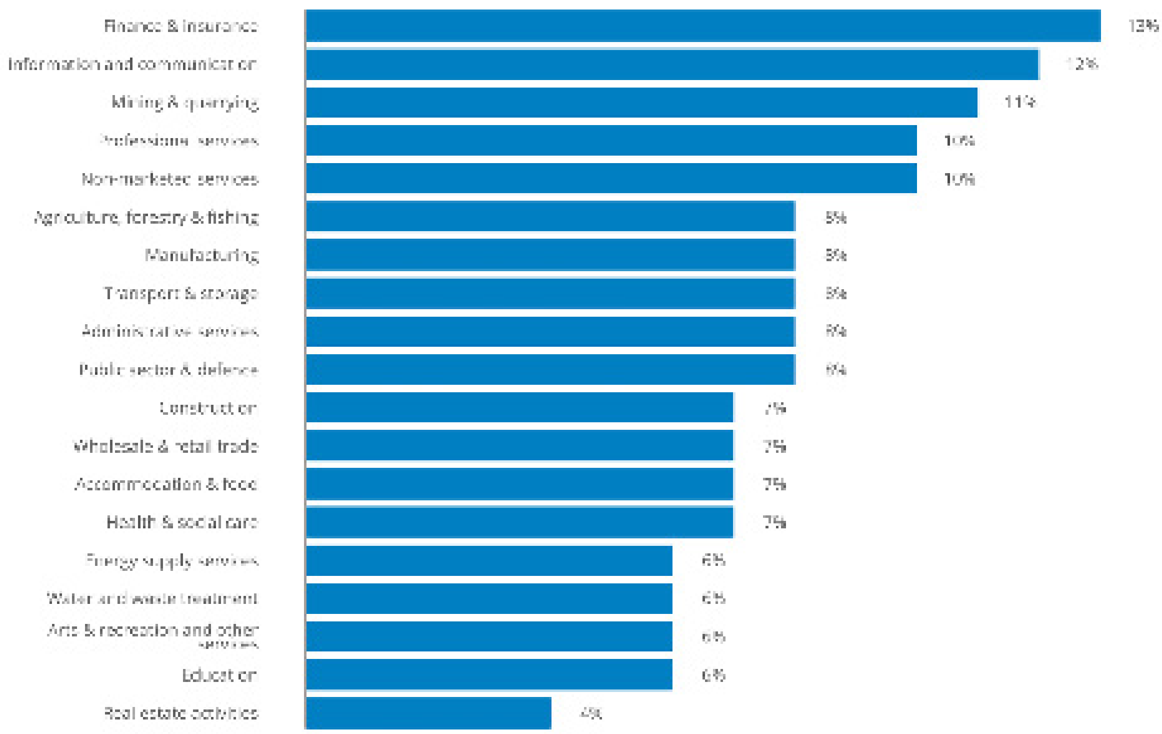


Source: European Skills and Jobs Survey, 2021, Cedefop

When respondents to the ESJS2 were asked if they now no longer undertake certain tasks as a result of new computer programmes and software being introduced, the following sectors stood out: agriculture, forestry, and fishing (where 51% of the respondents said they no longer undertook certain tasks), water and waste treatment (47%), mining and quarrying (45%), accommodation and food (45%), and finance and insurance (45%) (Cedefop, 2022). Looking more to the future, respondents were much more sanguine about the threat of machines taking over at least part of the tasks that they currently carry out (see Figure 3). Overall, around 35% of the workers expressed great or moderate concern that new digital or computer technology will take over some of the tasks they currently undertake. There was some sectoral variation with 13% of workers in finance and insurance reporting that part of their jobs may be taken over by automation, compared with 4% in real estate. When analysing the breakdown by education, less educated workers are more worried about job loss (41%), compared to those with middle (38%) or high (36%) education level. Regarding the regional distribution of the results, southern countries appear to have the highest fear of job automation, with Malta, Cyprus, Greece, Portugal, and Spain in the lead (Cedefop, 2022).

Complementing these sectoral perspectives about technologies doing part of the jobs, insights from Cedefop's ESJS2 (2022) highlights the impact of automation by occupation group. Market-oriented skilled agricultural, forestry, and fishery workers, building and related trades workers, elementary workers, as well as those in hospitality, retail, and other services, and personal service workers report the highest percentage of workers with some job tasks displaced due to new digital technologies. In contrast, legal, social, cultural and related associate professionals, health professionals, teaching professionals, sales workers, and general and keyboard clerks were least likely to have tasks displaced by new technologies.

Figure 3: Percentage of affirmative answers to the question 'To what extent do you think new digital or computer technologies in your company or organisation can or will do part or all of your main job?', by sector



Source: European Skills and Jobs Survey, 2021, Cedefop

Future perspectives

Evidence to date suggests that where AI affects jobs, it tends to free up time for the completion of other tasks and leads to wage increases (Felten et al., 2019). According to Brynjolfsson et al. (2023), the introduction of AI is associated with a 14% average increase in productivity, notably boosting performance by 34% for entry-level and low-skilled workers while having minimal effects on experienced and highly skilled workers. The ILO (2023) report assesses the global impact of generative AI, particularly Generative Pre-Trained Transformers (GPTs), on various occupations. Notably, clerical work faces the highest exposure, with 24% of tasks highly exposed and an additional 58% with medium exposure, raising concerns about surpluses in this occupation. The global employment effects vary across income groups, with low-income countries facing minimal exposure (0.4%) compared to high-income countries (5.5%). Gender disparities are evident, with more women potentially affected by automation.

Eloundou et al. (2023) analysed the impact of Large Language Models (LLM), such as GPTs, on employment by occupation, sector, wage level, education, and skills. They estimated that at least 10% of the tasks performed by 80% of the US workforce could be directly affected by LLMs. Specifically, around 19% of the workforce could have more than half of their job tasks affected by LLMs, with about 15% of tasks potentially being completed more efficiently. Thus, efficiency could increase by 47-56% when LLMs are combined with specialised software. Jobs that require a high skill level are most likely to have their content changed by the introduction of LLMs. Sectors such as manufacturing, agriculture, and mining – significantly affected by previous technological advancements – seem to be less vulnerable to LLMs compared to others. Accordingly, the 2022 labour shortages report suggests a positive correlation between these occupations, which are less exposed to automation, and labour shortages. In contrast, Eloundou et al. (2023) also find that jobs involving programming and writing are more likely to be affected than those requiring scientific knowledge and critical thinking. Occupations with the highest exposure include interpreters, translators, survey researchers, writers, authors, public relations specialists, mathematicians, web designers, financial analysts, accountants and auditors, legal secretaries, data managers, and proofreaders. A key question, of course, is whether the take-up of LLMs in industry will be as substantial as some commentators suggest.

A broader picture of the probability of automation and net impact on employment by occupation, worker, industry, country, firm, etc. is presented in Table 1 below, retrieved from Filippi et al. (2023).

Other evidence, based on projections of current trends, indicates that AI in its various forms could automate a wide range of human tasks, consequently leading to job displacement. Beyond the alarming headlines, the impact of AI may be somewhat less dire: an estimated 7% of current jobs are projected to be entirely replaced, 63% to be augmented by AI, and 30% to remain unaffected. McKinsey's 2023 report on Technology Trends (Chui et al., 2023) flags the expectation that over the next decade, automation in various forms will transform 20-30% of the hours spent on job related tasks. For example, generative AI has the potential to be deployed across numerous sectors, assuming responsibilities such as composing emails and other documents. Although specialised skills are required to develop cloud computing or machine learning, McKinsey anticipates the rate of technological advancement leading up to 2030 to be on par with or exceed that of the past century. If this materialises, it is likely to place considerable demands on education and training systems to produce the skills required.

The green transition will also be affected by technological change. In the energy markets, the widespread adoption of 'Smart Grid' technology will likely increase demand for roles related to grid management, data analysis, renewable energy integration, energy efficiency, cybersecurity, and data science. Regarding climate change, carbon sequestration adoption may lead to increased opportunities in environmental science, sustainable resource management, and climate change mitigation. Therefore, a shortage of labour and skills is likely to arise in these areas, as identified by the 2022 EURES report on labour shortages and surpluses.

Technology also has the potential to transform the nature of employment relationships and the extent of workers' attachment to the labour market. Over the past decade, the emergence of platform work has been witnessed (Eurofound, 2021). According to JRC (2020), platform work is a growing phenomenon in Europe, with an estimated 11% of the adult population having used a digital labour platform to find work. Additionally, it suggests that the rise of platform work can be attributed to the increasing availability of digital technologies, which have made it easier and cheaper to connect workers with customers. This has led to a significant increase in the number of platform workers, with some estimates suggesting that up to 30% of the workforce in some countries are now engaged in platform work. Noticeably, while platform work has the potential to boost participation in the labour market through better matching procedures, it also raises concerns about the lack of regulation and the lowering of the quality of employment. Also, survey data demonstrate that the scale of platform work has hit a plateau in Europe.

While platform work has gained attention, it remains a small portion of the workforce. Yet, the broader shift towards flexible, virtual work is a more impactful trend. Beyond digital labour platforms, traditional sectors are also experiencing the 'platformisation' of work. Advancements in technology have facilitated a rise in remote and flexible work arrangements, transforming employment structures. Examining digital devices, monitoring, and algorithms in diverse work settings, the findings of Fernandez Macias et al. (2023) highlight a notable proportion of workers subject to digital monitoring and algorithmic management.

It should be noted that change does not always occur as quickly as some analysts predict. Firms tend to be risk-averse when making large-scale investments in new technology, implying that the impact of advanced language models may not be as immediate and widespread as some experts suggest (Felten et al., 2019). A slower pace of technological advancement could have implications for the EU's future competitiveness and prosperity, potentially impacting employment rates, wages, and job quality. The Technology Adoption Life Cycle is a model that categorises adopters of a new innovation into five groups based on their willingness to try new technologies. The curve illustrates the diffusion process of an innovation over time. The five adopter groups, along with their approximate percentage distribution, are as follows:

- Innovators (2.5%): This group comprises the first individuals to adopt a new technology. They are risk-takers, often tech enthusiasts, and are willing to experiment with novel innovations.
- Early adopters (13.5%): Following the innovators, early adopters are quick to embrace new technologies. They serve as opinion leaders in their social circles and are key influencers in the adoption process.
- Early majority (34%): This group represents the average members of the population who adopt an innovation after it has been proven by the early adopters. They tend to deliberate before embracing new technologies.
- Late majority (34%): This group adopts innovations after the majority of the population has already accepted them. Members of the late majority are typically sceptical of change and adopt innovations out of necessity.
- Laggards (16%): Laggards are the last to adopt a new technology. They are resistant to change, often due to scepticism or a preference for traditional methods.

Table 1: Probability of automation and impact on employment by level of analysis – review by Filippi et al. (2023)

LEVEL OF ANALYSIS	PUBLICATIONS ESTIMATING THE PROBABILITY OF AUTOMATION	PUBLICATIONS ESTIMATING THE NET IMPACT ON EMPLOYMENT
Global level	49 % of the global work activities can be automated (Manyika, 2017)	Not analysed
International level	21 OECD countries: 9 % of jobs are automatable (Arntz et al., 2016)	Not analysed
Continental level	Europe: 54 % of workers are at risk of substitution applying the occupation-based approach (Bowles, 2014); 13.9 % applying the task-based approach (Pouliakas, 2018)	Not analysed
Country level	Substantial national differences in the distributions of workers based on the risk of substitution (e.g., Manyika, 2017)	The impact of automation technologies is not clear
	Explanatory factors: type of approach adopted, industrial and labour market structure, workplace organisation, past investment into automation, education of workers (e.g., Foster-McGregor et al., 2021)	Automation technologies in the long run (Autor and Salomons, 2018); Industrial robots in developed countries (Fu et al., 2021)
		Industrial robots worldwide (Carbonero et al. (2018)
		Automation technologies (e.g., Fu et al., 2021); Artificial intelligence (Mutascu, 2021)
Regional level	Significant variation in the probability of automation of European regions (Crowley et al., 2021)	The impact of automation technologies is not clear
	Explanatory factors: occupational structure, level of unemployment, level of development, industrial diversity, population density (e.g., Crowley et al., 2021)	Industrial robots in regions (e.g., Leigh et al., 2020); Artificial intelligence for middle-skilled workers in manufacturing firms (Xie et al., 2021)
		Industrial robots in communing or employment zones (e.g., Acemoglu and Restrepo, 2020); Artificial intelligence for low-skilled workers (Xie et al., 2021)
Labour market	Not analysed	The impact of automation technologies is not clear
		Automation technologies (e.g., Koch et al., 2019)
		Industrial robots (e.g., Chiacchio et al., 2018), only in the short run (Du and Wei, 2021), only in the manufacturing sector (Dottori, 2021)
		Industrial robots (Antón et al., 2020)
		Industrial robots only change the composition of employment (e.g., Caselli et al., 2021; Dauth et al., 2017)
Industry level	Considerable differences across industries and across countries (Chang and Huynh, 2016)	The impact of automation technologies is not clear
	Most exposed industries: agriculture, manufacturing, construction, trade, transport, accommodation and food services (e.g., Lima et al., 2021)	Automation technologies (e.g., Klenert et al., 2020), only in industries exposed to international trade and competition (Aghion et al., 2020b) and in service industries, 'making' sectors and complementary sectors (e.g., Mann and Püttmann, 2018); Industrial robots (Klenert et al., 2020); Artificial intelligence in medium-tech industries (Xie et al., 2021)
	Least exposed industries: education, health, arts, management, public administration, public utility services (e.g., Caravella and Menghini, 2018)	Automation technologies in the manufacturing sector and in "applying" sectors (e.g., Mann and Püttmann, 2018); Industrial robots (e.g., Acemoglu et al., 2020b)
		Automation technologies only change work organisations (e.g., Boavida and Candeias, 2021); Artificial intelligence (Acemoglu et al., 2020a)

LEVEL OF ANALYSIS	PUBLICATIONS ESTIMATING THE PROBABILITY OF AUTOMATION	PUBLICATIONS ESTIMATING THE NET IMPACT ON EMPLOYMENT
Firm level	Employment in the private sector (McGuinness et al., 2021)	The impact of automation technologies is not clear
	Firm size (e.g., Frenette and Frank, 2020)	Automation technologies (e.g.; Bessen et al., 2020); Industrial robots (e.g., Acemoglu et al., 2020b); Information technologies (Bessen and Righi, 2019)
		– Industrial robots (e.g., Ballestar et al., 2021)
		Industrial robots: their impact depends on firm characteristics: adopting firm or not, firm size, capital- or labour-intensive firm (e.g., Koch et al., 2019; Ni and Obashi, 2021)
		Automation technologies (e.g., Parschau and Hauge, 2020)
Occupational level	Occupations with a high probability of automation	The impact of automation technologies is not clear
	Many automatable tasks (e.g., exchange of information, selling, use of hands) (e.g., Arntz et al., 2016)	Industrial robots, for non-routine employment (e.g., de Vries et al., 2020); Artificial intelligence, for high-income occupations (Felten et al., 2019) and non-routine work (Tschang and Almirall, 2021)
	Examples: clerks, shop assistants, cleaners	Industrial robots, for routine employment (e.g., de Vries et al., 2020)
	Occupations with a low probability of automation	Industrial robots (Caselli et al., 2021); Artificial intelligence (Acemoglu et al., 2020a)
	Many non-routine work activities requiring e.g., perception and manipulation, analytic thinking, creativity, social intelligence (e.g., Arntz et al., 2016)	Most exposed occupations: office and administrative support, production, and delivery occupations (Vermeulen et al., 2018)
	Examples: managers, hairdressers, nurses	Least exposed occupations: healthcare, management, architecture and engineering, academia, and art (Vermeulen et al., 2018)
Worker level	Tenure, previous unemployment, demotivation (e.g., Pouliakas, 2018)	Most exposed workers: less-educated, young, women, and employed in more automatable occupations, especially in manufacturing industries (e.g., Blanas et al., 2019)
	Education, skills, salary, training (e.g., Frey and Osborne, 2017)	Less exposed workers: more educated, older workers and men, especially in service industries (e.g., Blanas et al., 2019)
	Gender, age, race, type of contract (e.g.,Pouliakas, 2018)	
Work activities level	45 % of the tasks can be automated (Chui et al., 2015)	Not analysed
	Most automatable tasks: physical work in predictable environments, data processing, and data collection (e.g., Manyika, 2017)	
	Least automatable work activities: management and development of people, application of expertise to decision making, planning, and creative tasks (e.g., Manyika, 2017)	

Hypotheses about the future

The foregoing discussion has outlined the potential direction of technological change and its prospective impact on employment and the nature of work up to the year 2030. There are potentially three drivers of future change:

1. technological change of a more conventional kind which has the potential to automate through, for instance, the use of robotics;
2. technological change which is linked more to the use of GPTs;
3. platform work which is facilitated by the kind of technologies included in (1) and (2).

The hypotheses sketched out below encapsulate the factors described above.

H1: Automation follows its existing trajectory

Automation – in the form of robots and similar kinds of technologies – will continue along its current trajectory in European labour markets. Change will be incremental. In general, it will be employment and skill enhancing. By 2030, it is expected that technological change will have created more jobs than it has destroyed. For the most part, workers will find that the tasks required of them in their current jobs will change rather than their entire jobs becoming obsolete, but some jobs will be destroyed – mainly lower skilled routine ones. There is a risk that the digital divide increases a little because technologies and digital processes used in everyday jobs become incrementally more sophisticated.

H2: The diffusion of AI increases

The use of AI becomes much more commonplace across Europe. The quick and wide-scale adoption results in deskilling within jobs (with impacts of real wage levels) and job losses in skilled and high skilled jobs. Accordingly, by 2030, there is a risk that AI will begin to constrain employment growth in Europe.

H3: Increasing platformisation of work and employment

The increasing digitalisation allows the tasks which comprise the production and service delivery process to be broken down into a discrete set of tasks which can be undertaken by those outside of a company's directly employed workforce. Digital labour platforms increasingly connect supply of and demand for work. By 2030 it is unlikely that a substantial share of people will be platform workers, but the share will have increased and is likely to be concentrated amongst younger people who either prefer this kind of work or have little alternative given that technological change has the potential to reduce recruitment by employers (they retain and retrain existing workers but engage in less hiring of new workers).

References

Acemoglu, D., and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Handbook of labor economics (Vol. 4, pp. 1043-1171). Elsevier.

Acemoglu, D., and Restrepo, P. (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society*, *13*(1), 25-35.

Acemoglu, Daron. 2002. 'Technical Change, Inequality and the Labor Market'. Journal of Economic Literature. Vol. 40. No. 1. American Economic Association. pp. 7-72

Adams, A. (2018). Technology and the labour market: the assessment. Oxford review of economic policy, 34(3), 349-361.

Arntz, M., Gregory, T., and Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The geography of trade and technology shocks in the United States. American Economic Review, 103(3), 220-225.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The polarization of the US labor market. *American economic review*, *96*(2), 189-194.

Autor, D. H., Levy, F., and Murnane, R. J. (2002). Upstairs, downstairs: Computers and skills on two floors of a large bank. ILR Review, 55(3), 432-447.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). Skill demand, inequality, and computerization: Connecting the dots. *Technology, growth, and the labor market*, 107-129.

Autor, D., and Salomons, A. (2018). Is automation labor-displacing? Productivity growth, employment, and the labor share (No. w24871). National Bureau of Economic Research.

Bárány, Z. L., and Siegel, C. (2020). Biased technological change and employment reallocation. Labour Economics, 67, 101930.

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. *The quarterly journal of Economics*, *122*(4), 1721-1758.

Bessen, J. E. (2016). How computer automation affects occupations: Technology, jobs, and skills. Boston Univ. school of law, law and economics research paper, (15-49).

Bowles, J. (2014). The computerisation of European jobs. Bruegel, Brussels.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The quarterly journal of economics*, *117*(1), 339-376.

Brynjolfsson, E., Li, D., and Raymond, L. R. (2023). *Generative AI at work* (No. w31161). National Bureau of Economic Research.Brynjolfsson, E., and McAfee, A. (2011). Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy. Brynjolfsson and McAfee.

Cedefop (2020). Assessing the employment impact of technological change and automation: the role of employers' practices. Luxembourg: Publications Office of the European Union. Cedefop research paper; No 79. http://data.europa.eu/doi/10.2801/173340

Cedefop (2022). *Challenging digital myths: first findings from Cedefop's second European skills and jobs survey*. Luxembourg: Publications Office. Policy brief. http://data.europa.eu/doi/10.2801/818285

Cedefop (2022). Setting Europe on course for a human digital transition: new evidence from Cedefop's second European skills and jobs survey. Luxembourg: Publications Office. Cedefop reference series; No 123 http://data.europa.eu/doi/10.2801/253954

Chui, M., Issler, M., Roberts, R., and Yee, L. (2023). Technology Trends Outlook 2023.

Cortes, G. M., Jaimovich, N., and Siu, H. E. (2017). Disappearing routine jobs: Who, how, and why?. *Journal of Monetary Economics*, *91*, 69-87.

Dauth, W., Findeisen, S., Südekum, J., and Woessner, N. (2017). German robots-the impact of industrial robots on workers.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), 1593-1640.

Deming, David.J. and Kadeem Noray (2019). STEM Careers and the Changing Skill Requirements of Work. Harvard University

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). Gpts are gpts: An early look at the labor market impact potential of large language models. *arXiv preprint arXiv:2303.10130*.

Ernst, E., Merola, R., and Samaan, D. (2019). Economics of artificial intelligence: Implications for the future of work. *IZA Journal of Labor Policy*, *9*(1).

Eurofound (2014), Drivers of recent job polarisation and upgrading in Europe: European Jobs Monitor 2014, Publications Office of the European Union, Luxembourg

Eurofound (2021), Initiatives to improve conditions for platform workers: Aims, methods, strengths and weaknesses, New forms of employment series, Publications Office of the European Union, Luxembourg

Eurofound (2021), The digital age: Implications of automation, digitisation and platforms for work and employment, Challenges and prospects in the EU series, Publications Office of the European Union, Luxembourg

Fernández-Macías, E., and Hurley, J. (2017). Routine-biased technical change and job polarization in Europe. Socio-Economic Review, 15(3), 563-585.

Fernandez Macias, E., Urzi Brancati, M.C., Wright, S. and Pesole, A., The platformisation of work, EUR 31469 EN, Publications Office of the European Union, Luxembourg, 2023, ISBN 978-92-68-01661-9, doi:10.2760/801282, JRC133016.

Filippi, E., Bannò, M., and Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. Technological Forecasting and Social Change, 191, 122448.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. Technological forecasting and social change, 114, 254-280.

Future Business Tech. (2022). The World in 2030: Top 20 Future Technologies. *Future Business Tech*. https://www.futurebusinesstech.com/blog/the-world-in-2030-top-20-future-technologies

Goldin, C., and Katz, L. F. (1998). The origins of technology-skill complementarity. *The Quarterly journal of economics*, *113*(3), 693-732.

Goos, M., and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics*, *89*(1), 118-133.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in Europe. American economic review, 99(2), 58-63.

Haslberger, M. (2021). Routine-biased technological change does not always lead to polarisation: Evidence from 10 OECD countries, 1995–2013. *Research in Social Stratification and Mobility*, *74*, 100623.

Hatzius, J. (2023). The Potentially Large Effects of Artificial Intelligence on Economic Growth (Briggs/Kodnani). *Goldman Sachs*.

Jaimovich, N., and Siu, H. E. (2020). Job polarization and jobless recoveries. Review of Economics and Statistics, 102(1), 129-147.

Josten, C., and Lordan, G. (2020). *Robots at work: Automatable and non-automatable jobs* (pp. 1-24). Springer International Publishing.

JRC (2020). New evidence on platform workers in Europe. Results from the second COLLEEM survey.

Katz, L. F. (2000). Technological change, computerization, and the wage structure. *Understanding the digital economy: Data, tools, and research*, 217-244.

Katz, L. F., and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. The quarterly journal of economics, 107(1), 35-78.

Levy, F., and Murnane, R. J. (1996). With what skills are computers a complement?. *The American Economic Review*, *86*(2), 258-262.

McGuinness, S., Pouliakas, K., and Redmond, P. (2023). Skills-displacing technological change and its impact on jobs: challenging technological alarmism?. *Economics of Innovation and New Technology*, *32*(3), 370-392.

Nedelkoska, L., and Quintini, G. (2018). Automation, skills use and training.

Pouliakas, K. (2018). Determinants of automation risk in the EU labour market: A skills-needs approach.

Saha, S., Mamun, K. A., Ahmed, K., Mostafa, R., Naik, G. R., Darvishi, S., Khandoker, A. K., and Baumert, M. (2021). Progress in brain-computer interface: Challenges and opportunities. *Frontiers in Systems Neuroscience*, *15*, 578875.

Sebastian, R., and Biagi, F. (2018). The routine biased technical change hypothesis: a critical review.

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