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A GENDER PERSPECTIVE ON ARTIFICIAL INTELLIGENCE AND JOBS: THE VICIOUS CYCLE OF DIGITAL INEQUALITY

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The worldwide artificial intelligence market is expected to increase enormously in the next few years. Because of AI's immense potential, virtually all industries will be affected by the implementation of AI systems, resulting in the digitalisation and automation of work processes. This will cause disruptive shifts in labour markets, in terms of the number and profiles of jobs in industries as well as worker skill requirements.

We take a gender perspective and analyse how gender stereotypes and gendered work segregation on the one hand, and digitalisation and automation (as a consequence of AI implementation) on the other hand, are entangled and result in a vicious cycle of digital gender inequality. We provide insights into the gender-specific impact of AI technologies, which is relevant for the mitigation of the potential risk of the creation of social inequality and exclusion. We show that existing empirical evidence already indicates that AI will not increase gender equality but will somewhat further exacerbate the gender inequality in labour markets, ranging from further horizontal and vertical occupational gender segregation to an increase in the gender pay gap. We summarise policy guidance and measures to decrease gender inequality in the future.

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1 Why a gender perspective on artificial intelligence and jobs is needed

Ever since Deep Mind's AlphaGo beat Lee Sedol, the world's best Go player, in four out of five games in March 2016, the hype around artificial intelligence (AI) has been hard to contain. AlphaGo's strategies were not pre-programmed; instead, the system taught itself to play by mimicking human strategies and subsequently using reinforcement learning in countless games against itself. In this historic contest between humankind and algorithm, humankind was for the first time inferior to a machine, and the notion that nothing can beat human intelligence, creativity and intuition was shaken profoundly. The human *"race against the machine"*, a term coined by Erik Brynjolfsson and Andrew McAfee in their book on the interaction of digital technology, employment and organisation (Brynjolfsson and McAfee, 2011), was shifted to a new level.

At the same time, hopes have been raised that AI will help overcome human limitations and shortcomings. Essentially, AI technology is software that operates autonomously without direct human control. It is interactive and can adapt to its environment. AI systems use algorithms to interpret structured or unstructured data. These algorithms resemble a recipe, including formulating a problem and an objective, as well as the logical sequence of steps to organise, process and analyse the data sets. AI has been classified as a general-purpose technology (Agrawal *et al*, 2019; Brynjolfsson and McAfee, 2017). The worldwide AI market is expected to grow to $59 billion by 2025, representing a significant increase from the $1.8 billion spent in 2016 (Servoz, 2019).

AI systems are encountered not only in the form of algorithms or automated decision systems but also in embodied robots. As chatbots, voice assistance systems, service robots, collaborative robots, autonomous vehicles or toys, these machines communicate with humans, often in natural language, responding to human behaviour and adapting to different situations. They follow pre-programmed rules and expected behavioural norms and are perceived as social actors. Hence, 'AI systems' refers to a broad range of intelligent machines, embodied or not, which are already relevant in almost every aspect of life and will gain even more impact in the future. Because of AI's enormous potential, virtually any industry will be affected by the implementation of AI systems, driving digitalisation and automation of work processes. Hence, AI systems can profoundly transform jobs. Their application allows work processes to be automated on shop floors and in administration and core management tasks. Specific jobs will be completely automated, new jobs will emerge, and almost all jobs will have at least some exposure to AI technology and automation, requiring new – digital – skills. This will cause disruptive shifts in labour markets, both in the numbers and profiles of jobs in industries and also in skills requirements for workers. Understanding the impact of AI technologies on labour markets also requires an understanding of automation, computerisation and digitalisation of jobs. In this paper, we are particularly interested in whether AI affects men and women differently. We analyse how gender stereotypes and gendered work segregation, on the one hand, and digitalisation and automation (as a consequence of AI implementation), on the other hand, are entangled and result in a vicious cycle of digital inequality.

Existing gender inequalities exhibit a systemic component that does not affect one specific aspect but, on the contrary, is intrinsic to the whole social structure, thus generating inequalities at very different levels. We provide a conceptual framework that helps to understand the complexity of the problem. We identify the main factors that constitute a vicious cycle of digital inequality and reinforce and stress the existing disparities. This analysis is necessary since mitigating potential risks associated with AI technologies, particularly the risk of creating social inequalities and exclusion, requires insights into how gender is inscribed into technologies and their applications. The High-level Expert Group on Artificial Intelligence (HLEG AI)[1] created by the European Commission addressed this risk of exclusion of potentially vulnerable persons and groups, such as women, in their ethics guidelines on trustworthy AI. Likewise, the HLEG AI requests policy measures to ensure equal opportunities in access to education and technology as a substantial dimension of trustworthy AI systems.

In section 2, we analyse – based on understanding the entanglement of gender, technology, and work – the impact of AI on job transformation from a gender perspective. Section 3 discusses how jobs are transformed through AI and whether women are more affected by these transitions. Section 4 outlines how skills requirements change through AI and how gendered education impacts women's access to training and technology, thus negatively impacting their career options. Section 5 analyses empirical evidence on whether AI increases the gender pay gap. Finally, section 6 proposes how policy should address the raised issues.

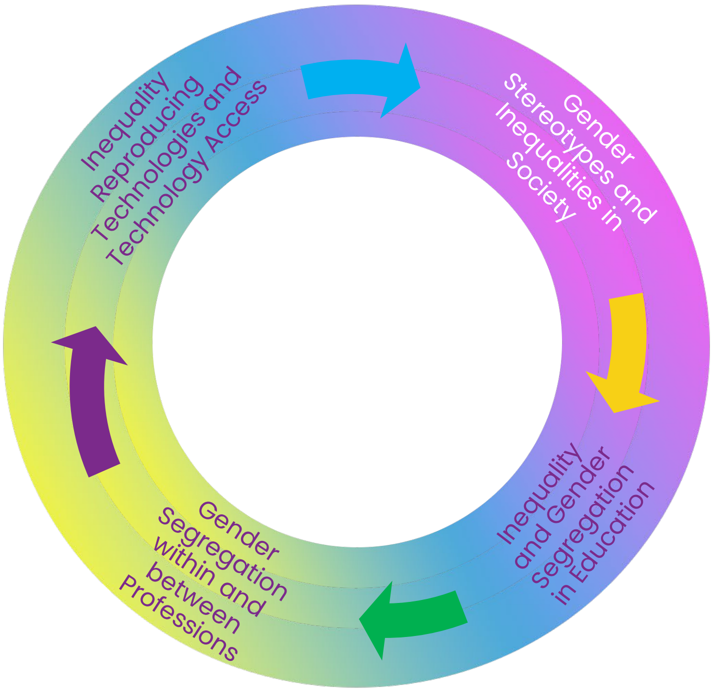
2 The vicious cycle of digital gender inequality

Underlying gender inequalities are a vicious cycle which is hard to break out of. To understand the whole problem, it is not sufficient to analyse labour markets only. Gender stereotypes and inequalities in societies are the root causes of early segregation of genders in education systems, resulting in only a few girls and women opting for education in science, technology, engineering and mathematics (STEM) and information and communication technologies (ICT). Thus, only relatively few women enter tech

[1] See https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai.

labour markets. Disparities in women's representation, remuneration and promotion make it extremely difficult to retain female talent in technology-related fields. A disproportionate number of women leave during their transition from higher education and career cycles. Consequently, homogenous (male) developer teams design AI systems and their applications, potentially neglecting the needs of diverse users and perpetuating gender stereotypes. UNESCO (2019) pinpointed how gendered technologies further create inequalities in access to technologies and aggravate gender inequalities in society. Figure 1 visualises this vicious cycle. Understanding how gender is deeply interwoven with work and cultural norms is crucial. A sustainable and effective strategy against gender discrimination must take measures at every stage of this cycle.

Figure 1: The vicious cycle of digital inequality



Source: Bruegel.

In the following sections, we dismantle this entanglement and provide empirical evidence from the European Union.

2.1 Gender Stereotypes and inequalities in society

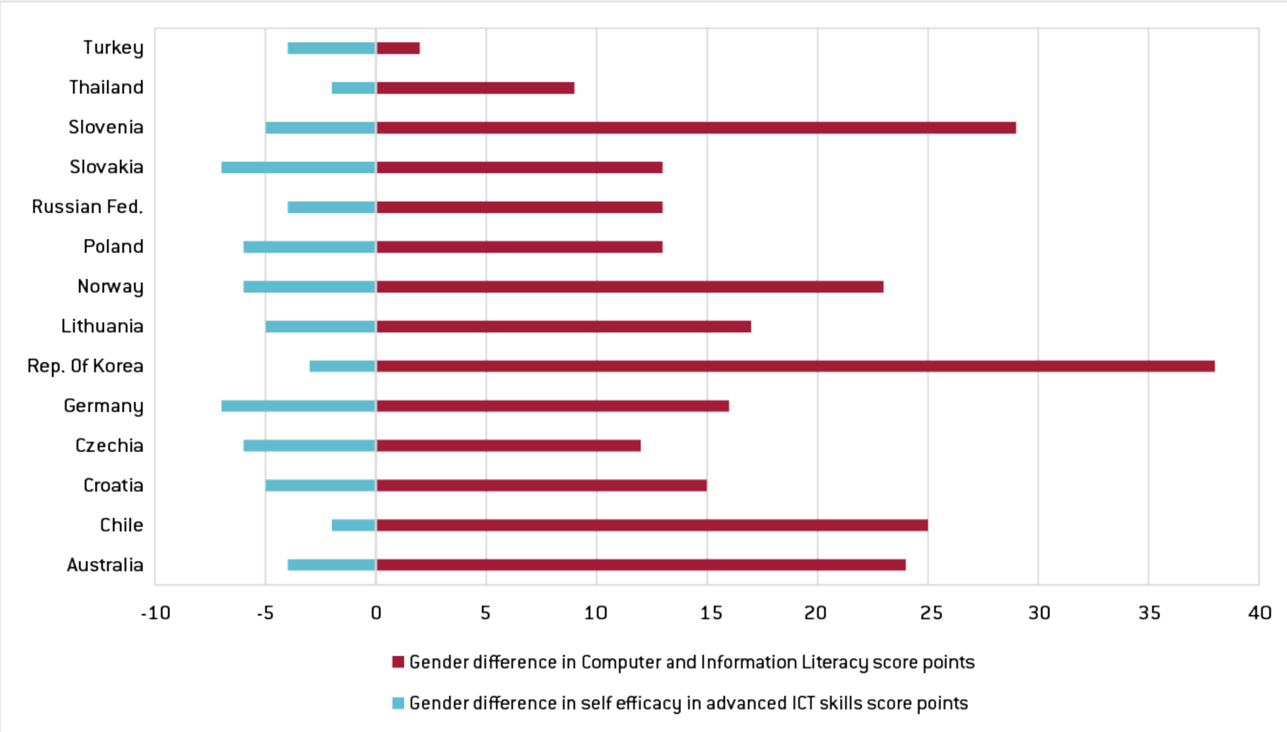
The vicious cycle of digital gender inequality is deeply rooted in the entanglement of work and gender: "*In short, doing gender and doing work, while analytically separable, appear to be empirically intertwined*" (Fenstermaker *et al*, 2002, p. 34). To understand the gendered division of labour, it is essential to scrutinise what is done at home and what is done at work, who does what and who is paid for what. Instead of casting gender as an attribute of individuals, West and Zimmerman (1987) reframed the concept of gender as "an accomplishment". They conceived gender as "*an emergent property of social situations: both an outcome of and a rationale for … justifying one of the most fundamental divisions in society*" (p.9). The fundamental shift in our theoretical understanding of gender from an attribute to an accomplishment shifts the attention to 'doing' and thus to gendered processes manifest in gendered structures (Acker, 1990). Gender has to be accomplished through social interactions and is also accomplished by how we distribute and do work.

One of the main areas of debate over women's position in the labour market is the relationship between women's role in paid and unpaid work (Bagilhole, 2002). The European Institute for Gender Equality (EIGE) summarised in critical findings on gender inequalities in the EU that there is a direct link between the unequal division of unpaid care in households and gender inequalities in the labour market (EIGE, 2020a). Women do the bulk of unpaid work in households: they do 2.6 times the amount of unpaid care and domestic work that men do (UN Women, 2018). Consequently, they have less time to access employment and grow their careers. Furthermore, within the labour market, women are found predominantly in certain occupations, which reflect the traditional division of roles in the domestic sphere. Traditional feminine occupations, including childcare, care for older people, nursing and education, are significantly less well-paid than conventional male occupations, such as construction, manufacturing or tech industries. The established social system leads girls and women to absorb unconsciously the idea that they are supposed to have certain qualities associated with the roles of domestic work and care. At the same time, boys and men are socialised into roles of 'breadwinners'.

2.2 Inequality and gender segregation in education

The different role socialisations of boys and girls lead to an overall reduction of talent in STEM subjects, undermining European industry's competitiveness. However, the gender gap in the educational choices of girls and boys only becomes visible in secondary and tertiary education. While girls and boys are nearly equal in their interest in STEM subjects in primary school (UNESCO, 2019), their interest develops in significantly different directions at later stages of education. At the age of 15, when choosing the field of specialisation in education, only 0.5 percent of girls, while 5 percent of boys, wish to become ICT professionals across Organisation for Economic Co-operation and Development countries (OECD, 2017). These gender-specific expectations exist independently of the actual performance of girls and boys in related subjects at school. Correll (2001, 2004) showed that *cultural beliefs about gender* skew the perceptions of girls' competencies and constrain their career aspirations. Compelling evidence of the impact of gender stereotypes is found in the *self-efficacy* gap in mathematics and digital competencies, or differences between girls' and boys' confidence and belief in their abilities. Although girls and boys do similarly well in maths and digital literacy tests until puberty, girls rate their skills significantly lower (UNESCO, 2019).

Figure 2: ICT abilities of girls and their perception of abilities



Source: UNESCO (2019).

Figure 2 shows that despite strong performance in computer and information literacy, girls do not have confidence in their ICT abilities. Unfortunately, the lack of self-confidence, structural barriers and prevailing gender stereotypes lead to selective educational choices. Girls predominantly choose humanities and social science majors, while boys choose computer science and engineering studies. The global proportion of female enrolments in education is 70 percent, in health and welfare 69 percent, in art and humanities 61 percent, in natural sciences (including biology) 56 percent, in STEM (average) 36 percent and ICT 29 percent (Equals Research Group cited in UNESCO, 2019, p. 23). In Europe, the numbers are even lower: Only 34 percent of STEM graduates and 17 percent of ICT graduates are female (European Commission, 2021). Only 2.4 percent of female tertiary graduates earn ICT degrees versus 9.2 percent of male tertiary graduates.

2.3 Gender segregation in professions

Although women can, in most places in principle, enter any profession they want, the segregation of men and women is reinforced in occupations. Professional aspirations are incorporated in the individual self-images children develop during socialisation from early childhood through adolescence. When comparing one's self-image with the image of a profession, gender plays a crucial role in career choices. When the gender image of a profession does not match the self-concept, the attractiveness of occupations and individual interests may be overruled by feelings of inadequacy (Haas *et al*, 2016). And even if women aspire to masculine jobs, social, cultural and structural barriers for women complicate careers in these occupations. As skills and competencies needed to do a specific job are inherently tied up with masculinity and femininity, gender is used as a discriminant criterion for hiring instead of looking at the actual competencies of potential employees (Lorber, 1994, p. 199).

Unfortunately, once in the field, women are again exposed to cultural biases within professions that contribute to patterns of retention and attrition (Carroll *et al*, 2016). Professional socialisation entails not only the mastery of skills and specialised knowledge of the profession but also requires a match between the profession's values and personal values and self-conceptions. Carroll *et al* (2016) showed how socialisation processes in the engineering profession lead women to develop less confidence that they fit into the engineering culture. Initiation rituals in coursework, informal interactions with peers and everyday sexism in teamwork and internships are particularly salient building blocks of gender segregation. Emily Chang (2018), a Silicon Valley insider, used the term *"brotopia"* for this phenomenon. She described how women face toxic workplaces with discrimination and sexual harassment. She argued that the "*aggressive, misogynistic, work-at-all costs bro-culture*" excludes women from technology development and access.

Apart from horizontal segregation into specific occupations, women also experience a glass ceiling effect resulting in vertical gender segregation. Women in STEM fields and the digital sector are less likely to hold high-level positions. According to UNESCO (2019), only one in every four leadership positions in tech industries (including non-technical positions in marketing, human-resource management and the like) is occupied by a woman. Chang (2018) cited cultural and structural barriers for women as the leading causes of this phenomenon.

ICT occupations are also held primarily by men (EIGE, 2020b). In the European Union, only 17 percent of ICT specialists are women. Although these figures vary across countries, with a balanced picture in Romania and Latvia, significant efforts are required in all EU countries to reduce segregation. The situation is not better for AI. In this field, men represent 84 percent of the EU workforce, with only a 16 percent share of AI-skilled women. Over the career path, the difference gets even more expansive. In positions that require more than ten years of AI experience, only 12 percent are occupied by women (EIGE, 2021). Notably, ICT and AI jobs represent a significant proportion of EU employment, and the demand for these specialists is only expected to grow. The low entry numbers of women into the field and the difficulties in progressing with their careers once in the area result in rather a homogeneous AI developer teams, which tend to reproduce and perpetuate gender biases in the technologies they develop.

2.4 Inequality-reproducing technologies and technology access

AI technologies are neither objective nor gender-neutral (Tufekci, 2015). The quality of AI applications depends mainly on the quality of the training data (in data-driven systems), the modelling (what we refer to as the algorithm), design (voice, shape and other characteristics of embodiment) and the actual implementation of the system in the specific context.

Hence, AI system designers determine which data and parameters are relevant for the training of the system, they decide on the operationalisation of performance indicators and goals, and they also decide on the AI system's appearance in its embodiments, their names, voices and characters, and on the roles and tasks they should take on.

Consequently, the initial social judgment of system designers is mathematically specified in algorithms, strategic goals and indicators for measuring systems' success. Thus, algorithms or AI systems refer, in fact to an undefined network of socio-technical arrangements in which the involvement of humans remains hidden at every step of the process. The terms 'algorithm' and 'AI system' obscure that cultural, societal and political values – and with them, potential discrimination and bias – are inherent in AI systems. O'Neil (2016, p. 53) expressed this pointedly: "*An algorithm is nothing more than an opinion formulated in a programming language.*" Hence, stereotypical notions of women and men and their tasks and roles in society are reflected by the machines designed in engineering labs.

The Berkeley Haas Center for Equity, Gender and Leadership, tracked available instances of bias in AI systems (Smith *et al*, 2021). Their analysis of 133 biased systems across industries from 1988 to 2021 found that almost every second analysed system demonstrated gender bias, and every fourth system exhibited both gender and racial discrimination. Training data for AI systems plays a crucial role in this. According to the principle garbage-in/garbage-out, AI systems learn what is in training data and once learned by an algorithm, will never forget. Smith *et al* (2021) identified several critical impacts of gender-biased AI. First, gender bias results in low quality for women and non-binary individuals. For example, voice recognition systems, increasingly used in many products and services, from autonomous cars to health care products, often work less well for women's voices. Such products or services could even threaten women's physical and mental wellbeing. Examples are AI systems supporting health diagnoses based on health data that does not represent gender appropriately. Second, gender bias in AI systems leads to unfair allocation of resources, information and opportunities for women. For instance, systems used in recruiting and hiring deprioritise women's applications (see also Bogen *et al*, 2018). Third, gender bias also perpetuates existing, harmful stereotypes and prejudices and leads to a "*derogatory and offensive treatment or erasure of already marginalised gender identities" (*Smith *et al*, 2021).

Smith *et al* (2021) referred here to examples of translation software or the use of the gender binary in gender classification, which builds an inaccurate, simplistic view of gender in tools such as facial-analysis systems. Hence, gendered AI systems impact individuals and also contribute to setbacks in gender equality and women's empowerment in societies. Saniye Gülser Corat, UNESCO's Director for Gender Equality, wrote, "*obedient and compliant machines posing as women enter our homes, cars and offices. Their hard-wired subservience affects how people speak to female voices and how women respond and express themselves in response to requests. To change course, we need to pay much more attention to how, when, and if AI technologies are gendered and who is gendering them*" (UNESCO, 2019).

Given this, it is unsurprising that access to technologies is also distributed unevenly across gender (UNESCO, 2019). Notably, the access gap can no longer be attributed to technology prices. There has been a significant decline in the price of connectivity and hardware, which has not been translated into a reduced gender gap (UNESCO, 2019). This problem is even more severe in developing countries. Available statistics show that women are about 50 percent less likely than men to be connected, controlling for age, education and income (World Wide Web, 2015). Although this problem is more severe in less-developed countries, there are also notable differences in Europe across regions. While western Europe has narrowed the digital usage gender gap, central and eastern European countries present an average gap of 3 percent, which is even higher for Greece. This comes as a consequence of skills and education being the most critical determinants of technological access. In parallel, experience with the use of technology contributes to a better understanding of its benefits and hence to a greater interest in accessing the required skills.

Further, the lack of skills fosters gender stereotypes and gendered work segregation of paid and unpaid work. Consequently, the cycle closes inevitably again. Different components in the vicious cycle influence each other, contributing overall to the persistence of inequalities over time.

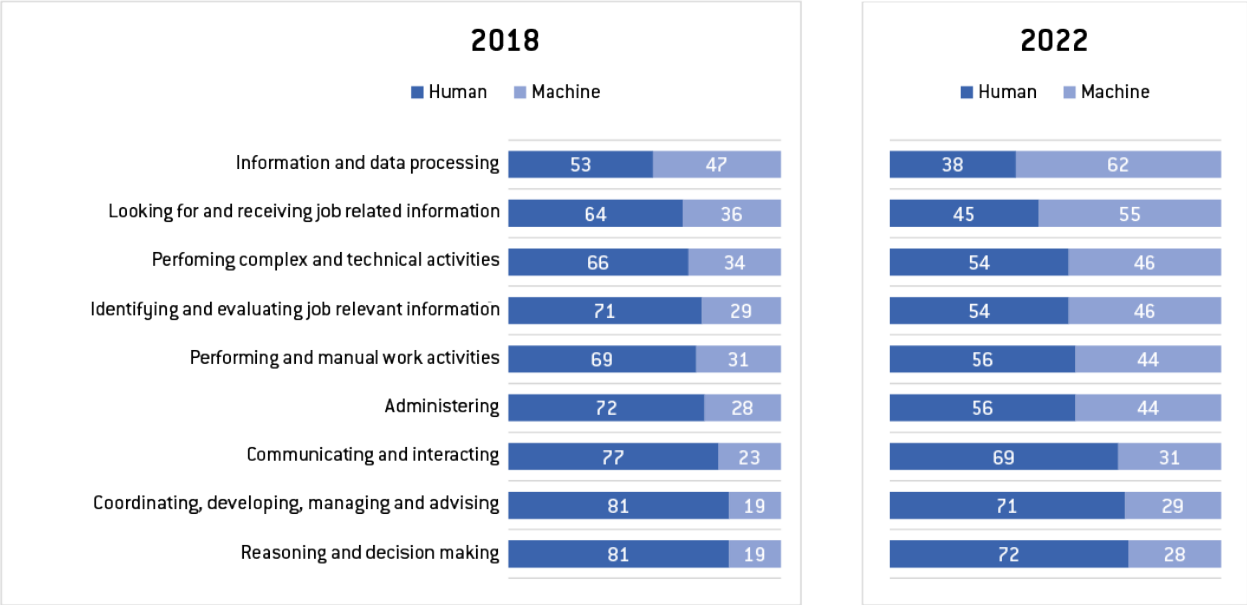
To ensure a smooth technological transition and the equal distribution of benefits derived from AI, proper diagnosis and understanding of the elements in the cycle that require further action is needed. In the following section, we provide a specific analysis of the transformation of jobs, skills and job segregation and the gender pay gap.

3 AI and the transformation of jobs

One of the most significant impacts of AI relates to the labour market. First, AI is expected to impact net job creation significantly. The so-called 'risk of automation' is present in all discussions about the future of work. The more pessimistic have predicted a rate of destruction of jobs because of AI and automation ranging from 30 percent (PwC, 2018) to 47 percent (Frey and Osborne, 2013). In addition, more than 60 percent of companies have accelerated their automation and AI capability building as a reaction to the COVID-19 pandemic McKinsey (2021). This combination of automation and AI has been called 'intelligent automation' and implies the replacement of a significant proportion of tasks. In parallel, a range of new, previously not-existing, jobs are being created. These relate to the need to implement and develop new technologies.

A second important implication of AI is the transformation of almost all occupations, at least to some degree. As a general-purpose technology, the impact of AI has a transversal nature, affecting all sectors of the economy. An essential challenge for policymaking is thus facilitating the proper integration between machine and human capacity in the labour market, i.e. to endow workers with the required abilities and skills to properly use the new technologies. The proportion of time devoted to work by humans and machines will be around 50 percent each in 2022 (WEF, 2020). Figure 3 shows this change for different tasks.

Figure 3: Ratio of human vs machine working hours, 2018 vs 2022



Source: Bruegel based on WEF (2020).

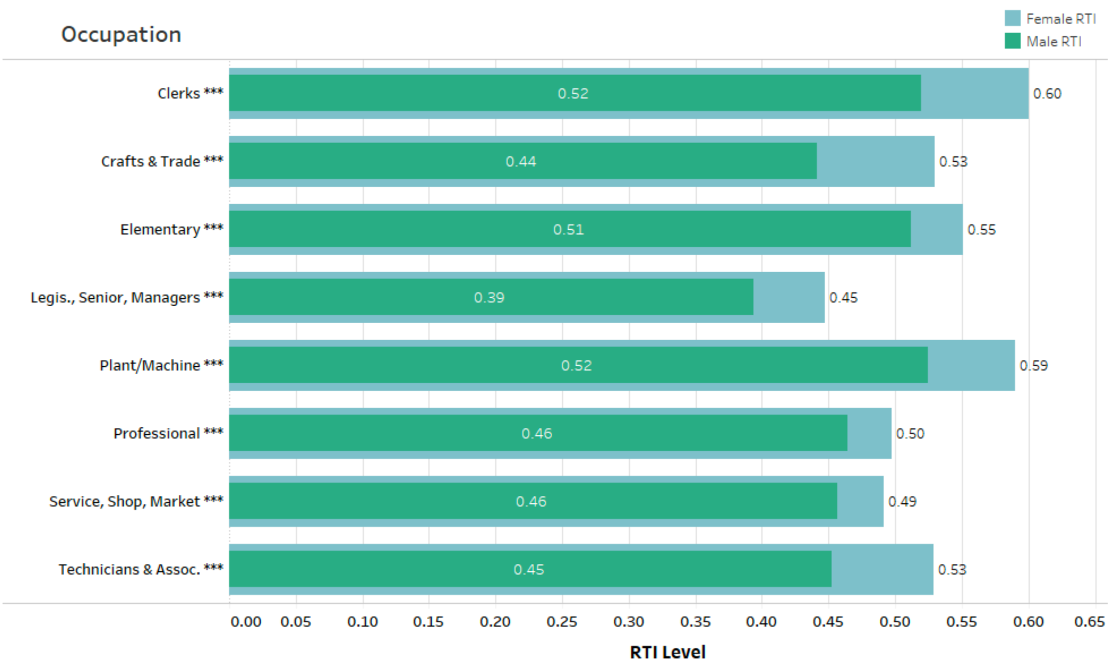
Avoiding asymmetries or exclusions is essential when helping different groups of workers adapt to these new sets of tasks. This can be achieved by reskilling and upskilling workers affected by the change while reducing the barriers to entry into new jobs. Even if most of the predictions about the future of work are optimistic, the transition will be challenging, and there is a strong need for policy guidance. Past episodes of economic and social integration of new technologies took several years or even decades. The sudden disappearance of a percentage of jobs and the creation of a new set of jobs implies significant economic disruption. It could affect different groups of people unevenly, with a more substantial impact on groups at risk of exclusion. The adjustment is expected to be slow, thus generating a mismatch of skills and technologies in the short and medium runs. Therefore, from a policy perspective, it is essential to look not only at the overall employment figures but also at the figures at a disaggregated level (regions, sectors, age groups, etc). Succeeding in the AI integration process requires the societal and market transformation to be adequately addressed at a profound level. The systematic nature of the gender inequality problem reflected in all stages of the vicious cycle is reinforced by the rapid growth of AI. The gender segregation women face in the education phase later creates a disadvantage for them in access to AI jobs, thus contributing to gender segregation within and between professions.

To determine the extent to which women are more negatively affected by the AI transformation than men, it is essential to identify the occupations at greater risk of replacement. Brussevich *et al* (2019) assessed the risk for men and women posed by automation, based on the Routine Task Intensity (RTI) framework developed by Autor *et al* (2003). Their study covered 30 advanced and emerging economies and showed an inverse relationship between female labour force participation and the RTI gap.

When women are more equally represented in workplaces, there is a more equal division of tasks between men and women. The study also showed that countries with smaller manufacturing sectors tend to have smaller gender RTI gaps, supporting research that services tend to be more gender-equal in employment than manufacturing. A detailed assessment of gender differences in RTI reveals that almost 13 percent of the gender RTI gap is explained by occupational choice, indicating that task types and job positions within occupations are the main drivers of gender disparities in routineness of work (Brussevich *et al*, 2019).

Brussevich *et al* (2019) also found that women, on average, perform more routine or codifiable tasks than men across all sectors and occupations. They perform fewer tasks requiring analytical thinking or abstracting (eg information-processing skills), resulting in a significantly higher risk of exposure to automation than men.

Figure 4: Male and female RTI in different occupations



Source: Brussevich *et al* (2019), p. 12. Note: RTI = routine task intensity. Bars represent respectively average male and female RTI indices for each occupation; *** *p*<0.01; ** *p*<0.05; * *p*<0.1.

There are, however, significant cross-country differences regarding women's exposure to automation. Within Europe, the gender routineness gap (the difference in the RTI values between men and women) is highest in eastern and southern European countries and lowest in Scandinavian and central European countries. And overall, 11 percent of the female workforce faces a high risk that their jobs will be automated, given the current state of technology. However, this probability is lower for younger cohorts of women and those in managerial positions (Brussevich *et al*, 2019).

These findings point to the following two important issues. First, self-selection by women into specific occupations explains a substantial part of the differences. Second, access to education and re-skilling and up-skilling for women already participating in labour markets is crucial to reducing inequalities. Both aspects will be addressed in the following sections.

4 Transformation of jobs and the need for re- and up-skilling

As noted in the previous section, vast technological developments and digitalisation have contributed to market shifts that are redefining industries. An immediate consequence of this transformation is the need to reskill workers. The transformation of tasks and occupations is associated with a change in the markets, where new skills requirements emerge while other skills become obsolete. One of the greatest threats facing organisations today is the talent shortage (IBM, 2019; Duch-Brown *et al*, 2021). The bottleneck holding up widespread adoption of AI technologies is the lack of data scientists and AI experts[2]. Importantly, this lack of AI skills could undermine Europe's industrial prospects.

Hence, the levels of AI adoption in a given economy depend mainly on the effective reskilling of its population. The ability to upskill and reskill the workforce is central to economic growth, with many adults lacking the right skills for new jobs (OECD, 2019). Moreover, the changing nature of work and the polarisation of the job market have created a situation that favours some geographical regions over others and some population groups that hold certain in-demand skills (WEF, 2020). This fact could create or enlarge existing gender, inter-regional, generational and income inequalities. Successful workers in this scenario will be those who can complement the work done by automated or algorithmic technologies and hence 'work with the machines'. This change in the distribution of tasks among people and machines presents substantial challenges for the European labour market (Servoz, 2019). Using machine learning and AI requires more analytical and digital skills from workers. In parallel, computers

[2] See for example Guntram B. Wolff, Julia Anderson and Paco Viry, 'Europe has an artificial-intelligence skills shortage', *Bruegel Blog*, 27 August 2020, https://www.bruegel.org/blog-post/europe-has-artificial-intelligence-skills-shortage, and Tom Tauli, 'How To Reskill Your Workforce For AI (Artificial Intelligence)', *Forbes*, 4 May 2019, https://www.forbes.com/sites/tomtaulli/2019/05/04/how-to-reskill-your-workforce-for-ai-artificial-intelligence/.

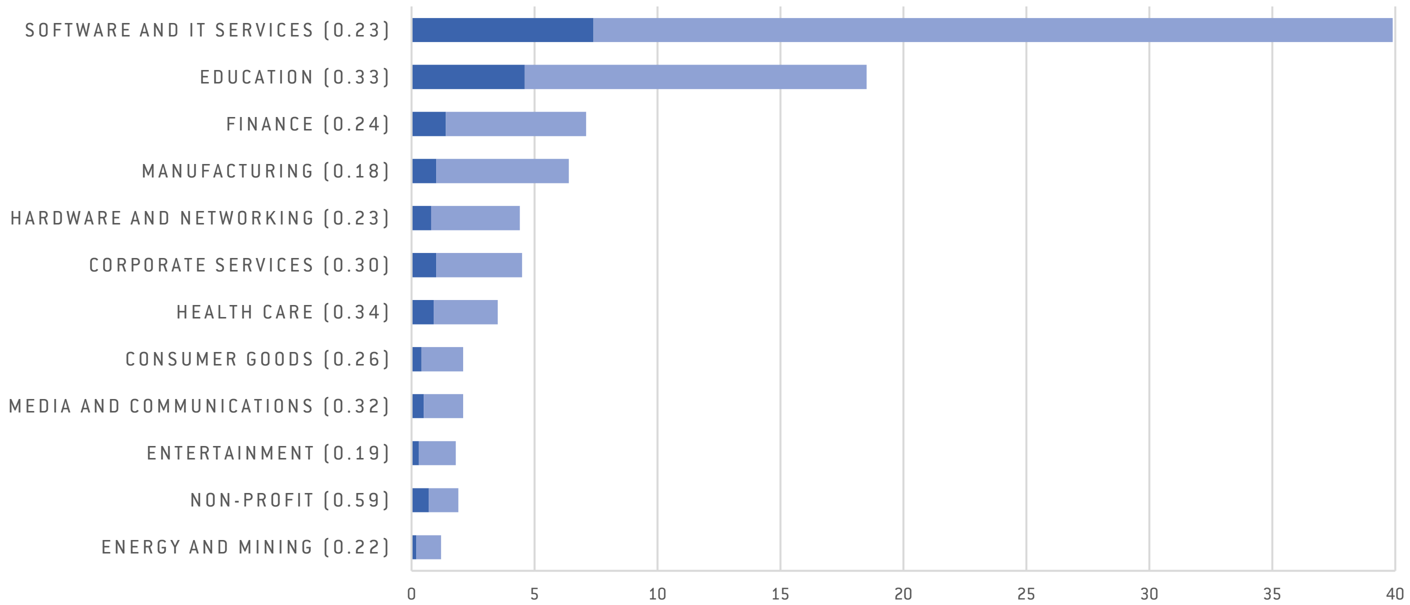
are still inferior at simulating human interaction, and tasks associated with higher social skills are more challenging to automate and replace. Thus, the assimilation of this technological transformation is highly connected to education. The success of the process will be determined by the quality of, and access to, reskilling, upskilling and re-training support.

The set of skills required for AI jobs is strongly related to maths (statistics, calculus, algebra, algorithms, probability), science (physics, cognitive learning theory, language processing) and computer science (data structures, programming)[3]. Such STEM skills are widely regarded as crucial to any given economy. Expanding and developing the STEM workforce is a critical issue for governments. Notably, the implications of reskilling are not neutral. Workers in STEM fields tend to be well paid and enjoy better job security than other workers (Hill *et al*, 2010). Deming and Noray (2020) showed that college graduates majoring in technology-intensive fields, including computer science, engineering and business, earn higher starting wages because they learn job-relevant skills already in school. Similarly, Duch-Brown *et al* (2021) used data on 420,000 jobs posted on a digital labour market platform to show that wages for AI projects are higher than for non-AI projects.

The STEM gap is also reflected in AI jobs. Figure 5 shows the distribution of AI talent across industries by gender. WEF collected the data in collaboration with LinkedIn. The gender gap in each industry is shown in brackets, where gaps range from 0 (no women) to 1 (parity). Noticeably, more than half of workers with AI skills work in software and IT services or in education, accounting for 40 percent and 19 percent of the total AI talent pool correspondingly. In each sector, women do not reach more than 7.4 percent and 4.6 percent respectively.

[3] See Verma *et al* (2021) for an exhaustive list of skills required in AI.

Figure 5: Distribution of AI talent across industries by gender



	Energy and Mining (0.22)	Non-Profit (0.59)	Entertainment (0.19)	Media and Communications (0.32)	Consumer Goods (0.26)	Health care (0.34)	Corporate services (0.30)	Hardware and networking (0.23)	Manufacturing (0.18)	Finance (0.24)	Education (0.33)	Software and IT services (0.23)
Female	0.2	0.7	0.3	0.5	0.4	0.9	1	0.8	1	1.4	4.6	7.4
Male	1	1.2	1.5	1.6	1.7	2.6	3.5	3.6	5.4	5.7	13.9	32.5

Source: Bruegel based on WEF and LinkedIn.

Intuitively, one would expect that the greater the level of gender equality in a given country, the greater the educational and empowerment opportunities for women in those countries, which would lead to greater engagement of girls and women in STEM fields (Williams and Ceci, 2015). Surprisingly, Stoet and Geary (2018) provided evidence for the opposite. They coined the term "*educational-gender-equality paradox*" to refer to the empirical finding that those countries with a higher gender equality index are paradoxically those where the number of women acquiring STEM degrees is lower. A large international database on teenage achievement showed that girls perform similarly to or better than boys on generic science literacy tests in most nations. Paradoxically, women obtained fewer college degrees in STEM disciplines than men in all assessed countries. Hence, the percentage of girls who would likely be successful in further STEM study is considerably higher than that of women graduating in STEM fields. This points towards a loss of female STEM capacity between secondary and tertiary education.

One potential explanation, the so-called affluent nations argument, is that generous welfare systems discourage women from self-employment and participation in labour markets. However, studies show that decisions relevant to career aspirations are made very early during secondary education, long before women enter the labour market (Corneliussen, 2021). Another explanation, suggested by Stoet *et al* (2018), is the *"individual choice"* argument, assuming that gender barriers have been removed in egalitarian countries and, therefore women's choices reflect their preferences. This argument has been criticised for ignoring the social, structural and cultural barriers that women face (see previous sections). Recent empirical studies instead point to a different explanation: that the combination of a prevailing masculine discourse on ICT and the lack of knowledge makes ICT an invisible career choice for women (Corneliussen, 2021). Breda *et al* (2020) argued that the *"individual choice"* argument is used in countries with higher levels of gender equality to legitimise horizontal gender segregation. In other words, particularly in countries with higher gender equality, there is a shift from vertical (the ratio of women decreases at higher hierarchical levels) to horizontal (men and women are directed to enrol in different educational domains) differentiation among genders as the latter type is culturally more acceptable. Breda *et al* (2020) also showed that cross-country differences in essentialist gender norms related to mathematics aptitudes and appropriate occupational choices could explain the gender paradox. They measured the stereotype *"math is not for girls"* using individual-level data on the attitudes towards maths of 300,000 15-year-old female and male students in 64 countries and showed that this stereotype is more robust in more egalitarian and developed countries and is strongly associated with various measures of underrepresentation of women in maths-intensive fields.

One of the primary purposes of this paper is to highlight the need for a deep understanding of the main challenges that proper skilling across genders faces in different countries. The fact that gender differences in STEM performance vary enormously across countries suggests the need for tailored and comprehensive policy action that considers all potential factors affecting the gap. This is especially important in the EU. Despite being considered a global leader in gender equality, the EU still shows a wide diversity of achievements at the national level. Eurofound and EIGE (2021) presented the evolution of EU gaps for 2010-2018. The report showed the disparity in performance, with Sweden ranking first in advancing gender equality and Greece performing least well. Among the countries that have accelerated the process are several Mediterranean member states and some Baltic countries. Several central and eastern European countries are on the other extreme of the distribution. Other countries, for instance, Czechia, Hungary and Poland, have remained stable over the whole period.

5 Occupational segregation and the impact of AI on the gender pay gap

One of the measurable consequences of the vicious cycle of digital inequality is the existence of a pay gap. As a result of the different stages in the cycle, we find occupation segregation still very high in Europe.

Despite the commitment of the European Union to the principle of equal pay for equal work or value, the difference between the average gross hourly earnings of working men and working women is still – with an average of 14.1 percent – substantial in Europe. This gender pay gap is only decreasing slowly. Among the countries with the widest gender pay gaps are Estonia, Latvia, Austria and Germany, while Luxembourg, Romania, Italy and Belgium have the narrowest gender pay gaps.

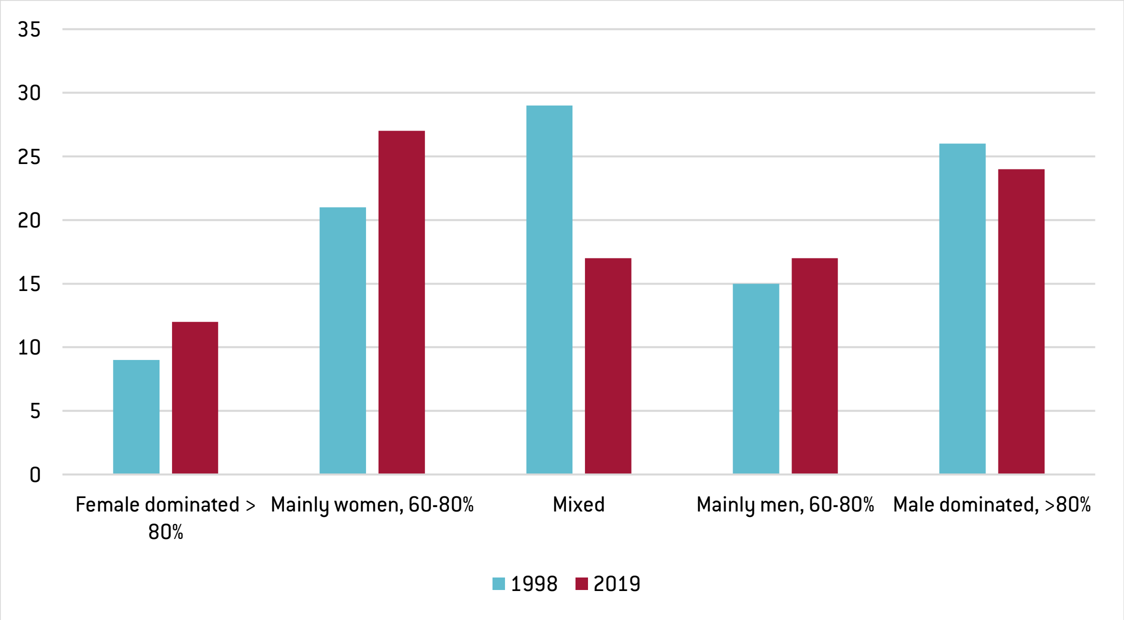
Observable characteristics such as part-time work, education and age/tenure contribute to a little less than one-third of the gap. The other two-thirds of the gender pay gap cannot be explained other than by gender discrimination.

One explanation for the difference in hourly wages between men and women is that women spend, on average, almost four hours more than men doing unpaid work in households and care (Eurofound, 2015). This unequal distribution of unpaid labour is reflected in labour markets, as one in three women reduce their paid hours to part-time, while only one in ten men do the same. Furthermore, women take charge of caring for children, leading to more periods out of the labour market, to career interruptions leading to negative impacts on (future) earnings and pensions. The gender pay gap widens in the top job-wage quintile (Eurofound, 2021).

There is also a consistent pattern in all European countries that men realise greater returns on their educations than women. This pattern becomes more pronounced the higher the qualification level. The most significant difference can be found among those with post-tertiary qualifications (Eurofound, 2021).

Another substantial part of the existing gender pay gap can be explained by occupational (horizontal) gender segregation (Bugligescu *et al*, 2020). The *European Jobs Monitor 2021: Gender gaps and the employment structure* (Eurofound, 2021) includes the following figure:

Figure 6: Employment share in the EU by gender concentration category, 1998 and 2019



Source: Eurofound (2021).

Female-dominated jobs, mixed and male-dominated jobs differ significantly in terms of their task profiles. Tasks associated with 'caring' (which implies low-technological content) are much more common in female-dominated jobs. In contrast, machine use (which means high-technological content) is much more common in male-dominated work. Eurofound (2021) also shows that ICT use, literacy, numeracy and autonomy tend to be higher in gender-mixed jobs and much lower in gender-dominated jobs. Moreover, these attributes are associated with cognitively demanding and higher-paid work.

Consequently, women are overrepresented in sectors such as education, sales and paid care, which offer significantly lower wages than occupations predominantly carried out by men. In their analysis of wage differences between men and women in different occupations using data from the European Structure of Earnings Survey (ESES) from 2006, Buligescu *et al* (2020) identified a relationship between occupational segregation and wages. They found a U-shaped relationship between occupational segregation and occupational wages when controlling for occupational characteristics: men earn relatively high salaries in occupations with either very few or many women. In diverse occupations, earnings for men and women are lower than in male- or female-dominated occupations. Women follow a similar pattern, but the effect is more substantial in the female occupations, giving men an advantage in the labour market (Bugliescu *et al*, 2020).

Aksoy *et al* (2020) provided the first large-scale evidence of the impact of industrial robots on the gender pay gap in European countries. Although they showed that robot adoption generally increases the earnings of men and women, it also increases wage inequality between men and women: a 10 percent increase in robotisation leads to a 1.8 percent increase in the gender pay gap. This effect can be explained by the rise in male earnings in medium- and high-skill occupations. These findings are mainly driven by countries with high levels of gender inequality and outsourcing destination countries and are independent of changes in the gender composition of the workforce. In other words, especially in those countries in which gender inequality is high, men disproportionally benefit from robotisation.

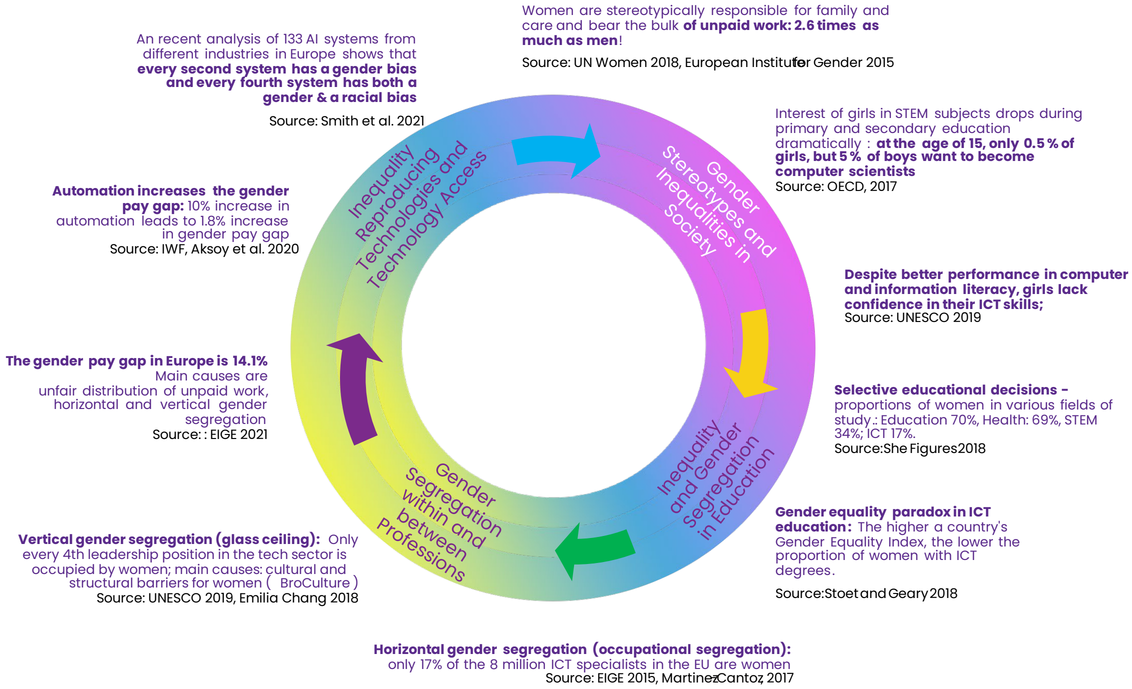
Gomez-Herrera and Müller-Langer (2019) analysed one of the largest EU online labour markets and found a 4 percent gender wage gap for male and female gig workers. They related this wage gap to the fact that women propose significantly lower wage bills, which increases the likelihood of winning the competition for contracts and the expected revenues of female gig workers.

Overall, there is still a significant gender pay gap in Europe, caused by unequal sharing of care and unpaid work, the horizontal segregation of men and women in the labour market, and the lack of women in leadership positions and occupations requiring analytical and technical skills. Existing empirical evidence shows that AI (reinforcing digitalisation and automation) will further exacerbate the gender pay gap in countries with high gender inequality but will have less adverse effects on wage inequalities in other countries.

6 Conclusion and need for policy guidance

We have set out the main challenges AI poses for the future of work in Europe from a gender perspective. We have described the existence of a vicious cycle of digital gender inequality, underpinned by empirical evidence from Europe (see Figure 7). This vicious cycle represents a systematic problem with notable implications at several stages of the social and economic structure. In what follows, we compile the main specific policy recommendations provided in the literature related to each step in the vicious digital inequality cycle. These recommendations are mainly offered by international organisms, including UNESCO, the OECD, EIGE or the Advisory Committee on Equal Opportunities for Women and Men (hereafter ACEOWM).

Figure 7: Vicious cycle of digital inequality with a summary of empirical facts



Source: Bruegel.

The first element in the cycle is the existence of gender stereotypes and inequalities in society. This is probably the most challenging aspect since it implies a profound transformation of societal beliefs and perceptions. It requires effective and concrete action at all levels of the communication process. A first necessary step would be the examination of exclusionary practices and languages (UNESCO, 2019). Similarly, the revision of content included in education systems and in the professional realm requires a significant effort at this stage (UNESCO, 2019). The eradication of these stereotypes is key for the achievement of subsequent milestones.

The second element that requires policy attention is the existence of inequality and gender segregation in education. The most important recommendation in this respect comes from UNESCO (2019) and points toward the increase in the exposure of women and girls to digital technologies in very different contexts (school, home, workplace, etc). UNESCO (2019) also suggested the need to integrate ICT into the curriculum at all levels of compulsory education. Similarly, it shows the advantage that some pedagogical strategies have with respect to others. More specifically, the use of collaboration and peer learning has proved particularly effective at engaging women with ICT. Finally, ACEOWM and OECD suggest the provision of incentives for women to participate in STEM education. For instance, raising awareness at an early career stage of the superior flexibility and working conditions of jobs in the AI sector could provide a notable incentive.

The third layer in the vicious cycle relates to gender segregation in occupations (horizontal) and hierarchies (vertical). In this respect, increasing the number of women in the AI workforce is urgent. ACEOWM proposes several actions, including, among others, increased transparency in the recruitment process, greater visibility for women in the AI field and the use of awareness-raising campaigns to incorporate the gender perspective into AI. Furthermore, it will be essential to pair measures related to labour-market participation with actions to foster better redistribution of unpaid childcare and housework and shape investment for better targeted life-long training. This implies providing additional services that allow parents to continue their career path during parenting periods.

Finally, the fourth concatenated element is the inequality in reproducing and accessing technologies. As detailed in section 2, the negative consequences of not achieving a sufficient degree of diversity in technology are magnified by algorithms. To prevent this, UNESCO provides concrete recommendations including, among others, the performance of 'algorithmic audits' to explore the sources of gender bias in AI technology, to examine how the gendering of digital assistants influences behaviour, or to develop methodologies to compare where, when, how often and for what purposes male assistants and female assistants are used (UNESCO, 2019). Relatedly, a specific UNESCO recommendation encourages governments to consider using universal service and access funds for investments in closing the digital skills gender gap[4].

All in all, we conclude that it is essential to support and guide the AI transition in Europe to achieve a balanced distribution of the loads and benefits it entails. A profound system transformation is required to avoid the perpetuation of gender inequalities over time. Close monitoring of potential symptoms of gender inequalities and asymmetries in the AI transition is strongly recommended to ensure early and effective action. Collecting gender-disaggregated data will foster evidence-based gender-related measures. Initiatives such as the OECD Gender Portal and the publication of annual Digital Gender Equality Reports will further help collect the evidence available in support of policy assessment, monitoring and benchmarking of progress made.

[4] See https://eige.europa.eu/gender-mainstreaming/toolkits/gender-impact-assessment/why-use-gender-impact-assessment.

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