



The Effects of AI on the Working Lives of Women



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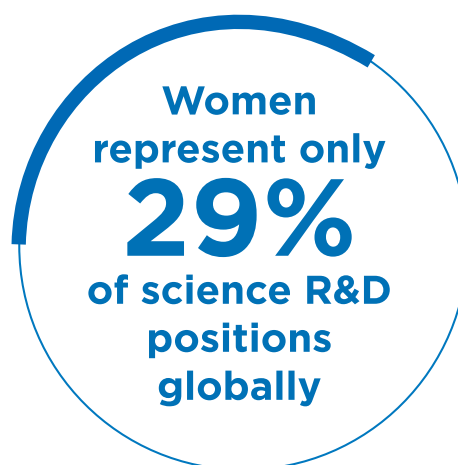
SHORT SUMMARY

Does AI advance gender equality?

Globally, studies show that women in the labor force are paid less, hold fewer senior positions and participate less in science, technology, engineering and mathematics (STEM) fields. A 2019 UNESCO report found that women represent only 29% of science R&D positions globally and are already 25% less likely than men to know how to leverage digital technology for basic uses.

As the use and development of Artificial Intelligence (AI) continues to mature, it's time to ask: What will tomorrow's labor market look like for women? Are we effectively harnessing the power of AI to narrow gender equality gaps, or are we letting these gaps perpetuate, or even worse, widen?

This collaboration between UNESCO, the Inter-American Development Bank (IDB) and the Organisation for Economic Co-operation and Development (OECD) examines the effects of the use of AI on the working lives of women.



By closely following the major stages of the workforce lifecycle – from job requirements, to hiring to career progression and upskilling within the workplace – this joint report is a thorough introduction to issues related gender and AI and hopes to foster important conversations about women's equality in the future of work.



The Effects of AI on the Working Lives of Women

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The authors are also grateful to those who shared their time and knowledge in shaping the case studies in the report, which demonstrate the importance of considering the impact of AI on women in different contexts and offer powerful examples of how technology can shape and be shaped by society. Thanks go to Dr. Gerasimos (Jerry) Spanakis, Professor Yana Rodgers, Professor Haroon Akram-Lodhi, Karla Skeff, Fábio Soares Eon, Marlova Jovchelovitch Noleto, Rafael Radke, Paula Leite, Glaucimar Peticov, Marcio Parizotto, José Mauricio Lilla, Karina Mea, Elena Arias, Claudia Piras, Yyannú Cruz, and Liliana Serrano.

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ABOUT THE ORGANISATIONS

This report complements the work of the three organisations behind it: the IDB, OECD, and UNESCO. These organisations advocate in several ways for inclusive and expansive digital futures. For more information on how these organisations are supporting the responsible use of Artificial Intelligence (AI) to promote gender equality, please see Annex.



IDB – Inter-American Development Bank

Established in 1959, the IDB is the principal source of financing for economic, social and institutional development in Latin America and the Caribbean (LAC). It provides loans, grants, guarantees, policy advice and technical assistance to the public and private sectors of its borrowing countries. In this context, through its technical co-operation scheme, the Bank supports the advancement of the ethical use of technology, in particular AI.

From the earliest discussion of the responsible use of AI and its potential to improve social well-being, governments in the region have turned their attention towards solving large-scale social problems such as education, poverty, and inequality. To the extent that AI becomes known as an accessible technology with application in daily life, its impact in terms of broader application to all aspects of human existence will become greater. AI applications are diverse, and their growth is noticeable in spheres of life where patterns can be detected among big volumes of data and complex models, and in the availability of interdependent systems that can improve decision-making and generate more egalitarian and efficient policies.



OECD – Organisation for Economic Co-operation and Development

The OECD works to build better policies for better lives. The OECD's goal is to shape policies that foster prosperity, equality, opportunity and well-being for all. The OECD draws on more than 60 years of experience and insights to prepare the world of tomorrow.

Working with governments, policy makers and stakeholders, the OECD establishes evidence-based international standards and finds solutions to social, economic and environmental challenges. From improving economic performance and creating jobs, to fostering better education and fighting international tax evasion, the OECD provides a forum and knowledge hub for data and analysis, exchanging experiences, sharing best practices, and offering advice on public policies and international standard-setting.

The OECD's work supports global collaboration to build trust in AI, benefit people and the planet, and monitor progress in accordance with the [OECD Principles on Artificial Intelligence \(AI\)](#). These promote AI that is innovative and trustworthy, and respects human rights and democratic values. OECD member countries adopted the principles in May 2019 when they approved the OECD Council Recommendation on Artificial Intelligence. The OECD AI Principles are the first to be endorsed by governments. They include concrete recommendations for public policy and strategy, and their scope ensures they can be applied to AI developments around the world. The OECD.AI Policy Observatory, launched in February 2020, aims to help policymakers implement the principles.



UNESCO – United Nations Educational, Scientific and Cultural Organization

UNESCO seeks to build peace through international co-operation in education, science, culture, communication and information. UNESCO's programmes contribute to achievement of the SDGs defined in Agenda 2030, adopted by the UN General Assembly in 2015. By promoting openness and the innovative use of digital technologies for sustainable development, UNESCO's Communication and Information Sector seeks to reduce the digital divide and foster an inclusive digital transformation that respects, protects and promotes human rights.

As AI applications continue to expand opportunities to achieve the SDGs, UNESCO works to harness these in its fields of competence and lead reflection from a human rights and ethics perspective around concerns related to the rapid development of AI. The Organization focuses on empowering its Member States, promoting gender equality in the AI sector and combating algorithmic bias through raising awareness, setting standards, international co-operation, serving as a laboratory of ideas and building capacities of stakeholders.

Together with its Member States and partners, UNESCO engages with governments, the private sector, civil society and academia to facilitate a human-centred digital transformation that leverages emerging technologies, including AI, while defending human rights. Its Recommendation on the Ethics of Artificial Intelligence, the first global standard-setting instrument of its kind, was adopted by UNESCO's General Conference at its 41st session in 2021, with emphasis on gender equality.



Minderoo Centre for Technology and Democracy, University of Cambridge

The Minderoo Centre for Technology and Democracy is an independent team of researchers at the University of Cambridge who are rethinking the power relationships between digital technologies, society and the planet. Minderoo has four goals in this research: 1) Enhancing public understanding of digital technologies and their societal effects; 2) Exposing the global environmental consequences of digital technology; 3) Proposing solutions for the harmful impacts of digital technology on workers' rights; and 4) Building informed trust in digital technology and asserting the primacy of democratic values over corporate interests.

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EXECUTIVE SUMMARY

Artificial intelligence (AI) is “a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy” (OECD, 2020). AI is rapidly being integrated into both workplace and domestic settings. The world of work is changing as a result.

The use of AI technologies will affect women’s opportunities for work, and their position, status and treatment in the workplace. Around the globe, women in the labour force earn less than men, spend more time undertaking unpaid child- and elder-care jobs, hold fewer senior positions, participate less in science, technology, engineering and mathematics (STEM) fields, and tend to hold more precarious jobs overall. In harnessing AI, governments, institutions and companies must narrow gender gaps rather than perpetuate or exacerbate them.

This report, by the IDB, OECD and UNESCO, outlines current knowledge of the impact that AI systems have on women’s opportunities for work, and their position, treatment and status in the workforce. It does so by exploring how AI is used within and outside the workplace, and how it could be used in the future. It looks at the potential impact of new and emerging AI technologies on the skills that employers will require, on how women look for and are hired for jobs, and on how jobs are structured through automated monitoring and oversight. The report maps the opportunities and challenges that AI presents for the working lives of women and highlights the complexities that varying national and regional contexts present for understanding the impact of AI on the work of women. The report also notes that current research does not offer a complete or definite picture of how AI impacts the working lives of women and calls for further research and analysis in this area.

The report offers six findings:

- 1. Reskilling and upskilling women workers** – AI is changing the labour market, bringing new skill demands to workers of the future. It is crucial that women are not left out of the increased demand for professionals in STEM/AI. Programmes that support reskilling and upskilling women will help them access these fields. Digital skills will also be important for workers to understand the systems being implemented and raise concerns when necessary. The existing gaps in women’s access to these skills and jobs are troubling, and societies should work to narrow and eventually close them. This is the responsibility of governments, NGOs, academia, trade unions and the private sector.
- 2. Encouraging women in STEM** – More women at the forefront of AI design and development will be a significant step forward. To get more women leading in AI and technological development, governments, institutions, organisations and companies should support the education of women and girls, in STEM education in particular.
- 3. Accounting for contextual and cultural complexity** – AI systems have different impacts in different contexts and countries. Diverse labour markets, economies, cultures and gender norms shape how workers experience AI systems, meaning that AI-based tools and technologies will impact the working lives of women in a variety of ways. These contextual and cultural complexities should be addressed systematically when designing and implementing AI systems or policy and regulation responses to AI.
- 4. Leveraging multi-stakeholder approaches** – Governments, private sector companies, technical communities and academia need to engage these issues and take responsibility for the impact of AI tools and systems. Governments should create

and promote policies that consider the potential impact of AI systems on vulnerable groups. Organisations and institutions have a role in supporting skill-equalising work environments for women.

5. Shaping gender stereotypes – This report shows the powerful connection between stereotypes surrounding women’s paid and unpaid work, and how these can be both shaped by and encoded into AI systems. For example, virtual personal assistants might promote certain gender stereotypes, particularly around care and assistance. The role of women at work, and their often unpaid and unequally distributed domestic and care responsibilities must be more thoroughly considered when creating equal work environments for women, as well as in the design, policy and implementation surrounding AI technologies.

6. Continuing applied research – More applied research is needed on how AI systems impact work in general and the working lives of women in particular, and to understand potential societal impacts of widespread use of specific AI systems. For example, Chapter 3 highlights the differing effects on men’s and women’s job opportunities when AI hiring systems are rolled out with key questions left unanswered. Chapter 4 shows the lack of research surrounding the impact that AI monitoring systems have on the working lives of women and their opportunities for recognition and promotion. Going forward, organisations and governments should be transparent about how their AI systems function. Further research in this area will be required to catalyse the explainability of AI systems’ function and protect employees engaged with AI.

While emerging AI systems could present further challenges to the work of women, these impacts are not yet inevitable. This report aims to encourage organisations, the public, policymakers and academics to grasp the opportunities and be proactive in facing the potential challenges. Designing and deploying novel technologies, guided by a principles-based approach and best practices, will both help ensure that today’s gender stereotypes are not built into tomorrow’s technological systems and help close gender gaps.

More research in this area should cover system design, functionality and – most importantly – social and cultural impact. Research can help ensure that the application of AI in the workplace does not create feedback loops that encode existing gender bias. It can also help address global disparities in knowledge about AI systems across country and regional contexts.

Most existing research about AI focuses on advanced economies, usually in the Global North. As social and economic contexts vary by country, this lack of regional representation can exacerbate inequalities in the ethical design and deployment of AI. As the cases in this report show, there are lessons about the benefits and harms of AI in a range of global contexts.

Technological advances bring productivity gains, but all individuals’ talent must be developed for these gains to be fulfilled. The design of technologies, the gendered gaps in data, and the speed, scope and scale enabled by AI can make matters worse for women workers if there is no active attention to this issue. Preparedness for the future means governments, organisations and all employees – not just women – must understand the challenges and opportunities that new types of AI technologies present and how these can lead to fair and equitable work.

INTRODUCTION

The world of work is transforming rapidly. Artificial intelligence (AI) technologies are being integrated into many workplace and domestic settings. While women's labour force participation rates increased around the globe in the 20th century, there remains much to be done to achieve gender equality within and outside the workplace.

This report, by the IDB, OECD and UNESCO, outlines current knowledge of the impact that AI systems do and could have on women's opportunities for work, and their position, treatment and status in the workforce. It defines, discusses and frames the emerging challenges and opportunities AI presents for women in the workforce.

The aims of the report are to:

- > **Raise awareness** about the prevalence, technical functionality and potential consequences of AI systems, and to document the current and possible effects of AI on women in the workplace.
- > **Show the varied and widespread effects of AI on women** at every stage of, as well as outside of, the functioning of labour markets, using case studies from around the globe.
- > **Outline specific challenges and opportunities of emerging AI technologies** for women at different career stages. This includes women's entry and re-entry into the labour force, women's upskilling and reskilling, and career development and promotion.

The report uses "AI technologies" to refer to machine-based systems that can make predictions, recommendations or decisions influencing real or virtual environments. This might include, for example, automated systems to sort job applications or new ways to measure and monitor productivity at work. By referring to AI technologies as systems, this report shows how data inputs, methods of data analytics and the use of technologies in practice combine to create systems that rely on social and technological elements. When this report considers AI technologies, it is not as systems without any human input or oversight. Rather, it is how these combined social and technological elements work together and not least the economic and the ethical factors shaping the mix. This combination of uses of new technologies presents both opportunities and challenges for women in the workplace.

The report provides a review of existing research and literature to help decision-makers across sectors and stakeholder groups – including policymakers, those in the public and private sectors, trade unions, the technical community and academia – address the path ahead, covering the challenges and opportunities that AI presents to the working lives of women.

Chapter 1 outlines the opportunities and challenges that AI presents in five key areas surrounding the working lives of women: (1) access, connectivity and digital skills; (2) women in AI; (3) reskilling and upskilling; (4) gender stereotypes; and (5) algorithmic transparency. It argues that opportunities lie in investing in women's access to digital devices, reskilling and upskilling programmes, using AI design and implementation to challenge gender stereotypes, and for more research into the impact of AI on the working lives of women.

Chapter 2 illustrates that there is currently no definitive answer about how AI-driven automation will alter women's jobs. However, given that AI can automate even complex, non-routine tasks, governments and organisations need to focus on giving women the opportunity to develop digital skills, AI skills and non-automatable competencies such as interpersonal skills. This is where the main skilled labour opportunities will lie in the jobs of the future.

Chapter 3 discusses the effects of how women learn about, search and apply for jobs. The focus in this chapter is on AI hiring systems and AI job targeting systems. It notes that, while AI can reduce gender bias in job descriptions and hiring, not enough is known or understood about the design and impact of these systems to determine the nature of the effects and likely trajectory. Therefore, more applied research is needed on the design and outcomes of AI hiring systems and their impact on vulnerable groups, including women and on those who are disadvantaged by historical inequities related to various factors.

Chapter 4 considers AI systems (including monitoring systems) that impact women's status, treatment and opportunities within the workplace. It points out that these often encapsulate and reinforce gender stereotypes around labour, care and domestic work.

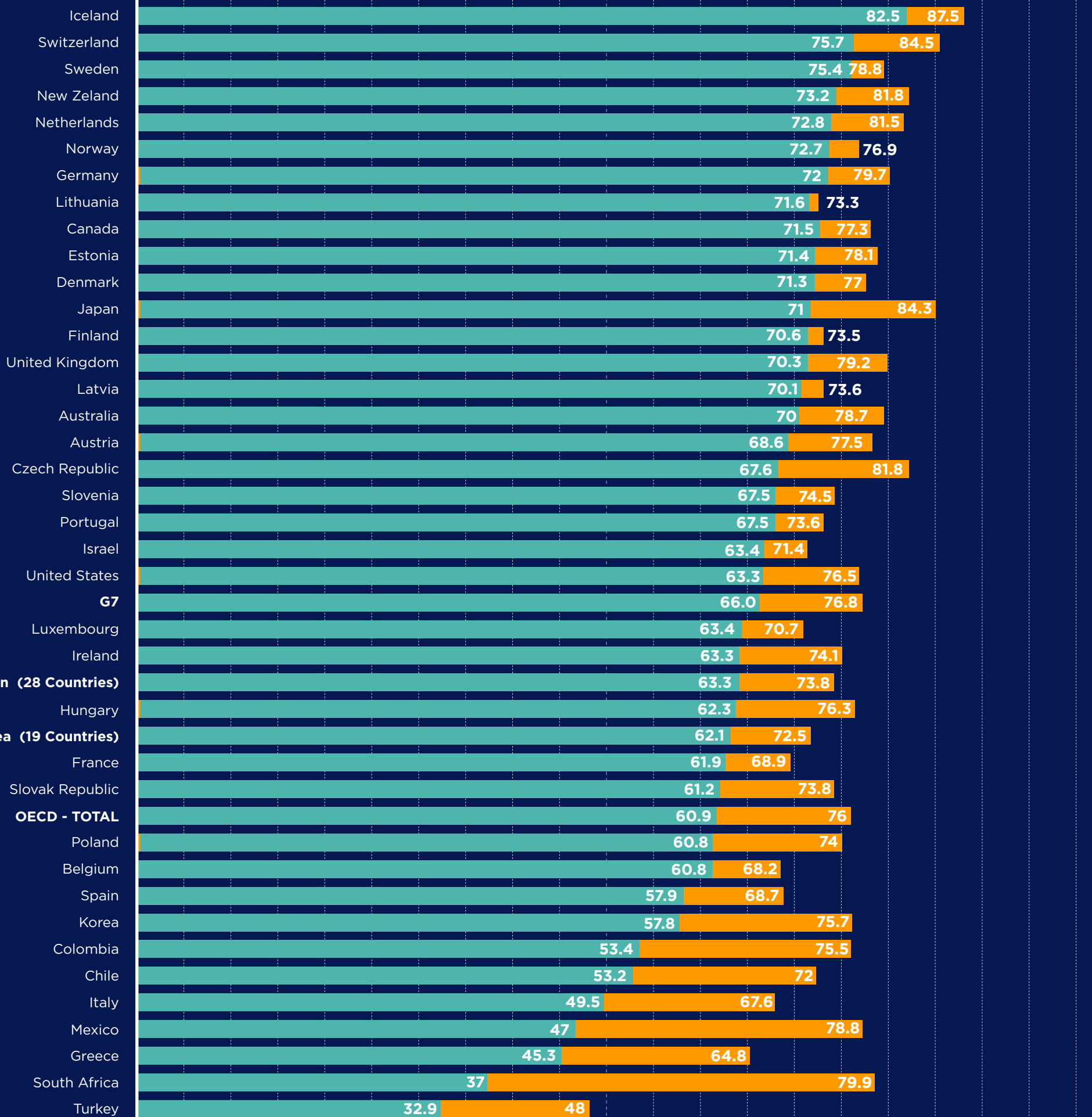
The report highlights that current research does not offer a complete or definite picture of how AI impacts the work of women. It shows how different labour markets, economies, cultures and gender norms shape how workers are impacted by and experience the effects of new technologies. However, the potential impacts that this report outlines are not inevitable. Instead, the study shows other potential paths ahead and encourages the private sector, civil society, policymakers, workers and academics to grasp the opportunities and proactively address the challenges that arise.

Gender inequality in the labour market

Contextual factors shape how men and women experience changes to their work that AI brings about. For example, gender inequalities in labour force participation rates and pay gaps shape the context for the introduction of new AI technologies. Women often earn less (ILO, 2019; Ortiz-Ospina & Roser, 2019; World Economic Forum, 2021), hold fewer senior positions (Catalyst, 2020; UN Women, 2021) and tend to hold more precarious jobs (European Parliament, 2020; M. C. Young, 2010). Women tend to spend more time undertaking unpaid child- and elder-care jobs and domestic work, and participate less in science, technology, engineering and mathematics (STEM) fields (Bustelo et al., 2019).

Although the gap between men and women in labour force participation is closing, progress remains uneven. OECD data from 2017 noted that, while significant improvements had been made in some parts of Latin America, large gaps remained in workforce participation. These also remained in parts of the Asia Pacific, Africa and Europe (Soto, 2020). OECD data from 2019 (Figure 0.1) showed a consistent gender gap in employment globally.

Figure 0.1
Gender gaps
in employment



Sources:
OECD, 2021a.

It is not just the gap in employment that stifles gender equality at work, but also the type of jobs that men and women hold. Women tend to have lower quality jobs than men and work in sectors that are less productive. Their jobs are also less secure. Women are paid less and face higher risk of unemployment (Soto, 2020). Therefore, increasing women's labour force participation alone might not increase gender equality at work. Reducing gender-based employment segregation is key to improving job quality and gender equality, especially if employment segregation means that women crowd into a limited number of lower-skilled, lower-quality occupations with lower wages.

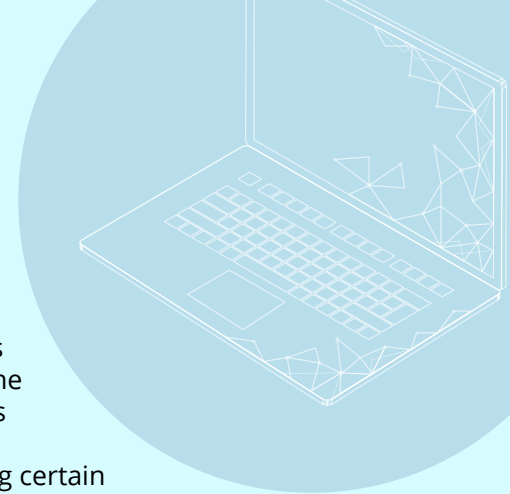
Considerations and limitations of this report

While this report focuses on the paid dimension of labour, it acknowledges that AI systems also impact women in their unpaid work. Women's disproportionate engagement in unpaid labour was exacerbated by the COVID-19 pandemic (Borah Hazarika & Das, 2021; Craig & Churchill, 2021; Del Boca et al., 2020; Giurge et al., 2021; Hupkau & Petrongolo, 2020; Power, 2020; Sarker, 2021). While this report touches on the challenges and opportunities that AI presents surrounding stereotypes and norms of unpaid care and domestic labour, further research and analysis are needed.

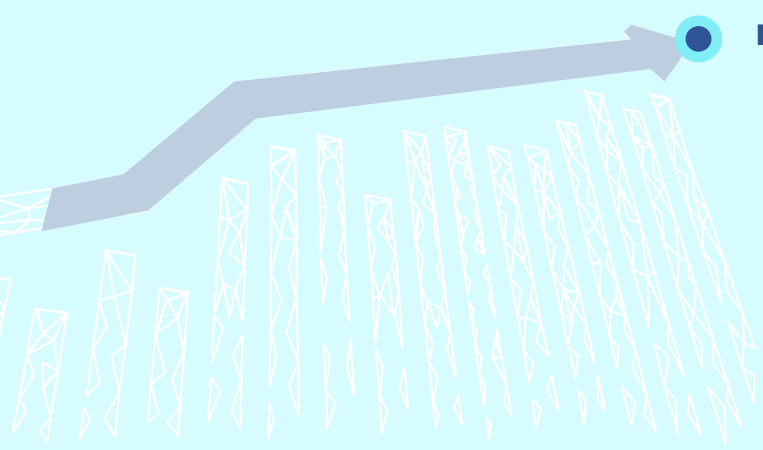
Further, the report includes examples from around the world to examine the potential impacts, opportunities and challenges of AI in the context of both the Global South and Global North. The different speed of technology adoption between Global North and Global South points to varying patterns in future transformations. For example, in Latin America, the level of workforce preparedness, the lower labour cost, the fact that most companies are small and medium-sized, and the frequently fragile infrastructure and credit markets can restrict innovation (Bosch et al., 2019). That said, a limitation of this report is that disparities in funding, resources and available data cause a prevalence of examples and research covering the Global North, and professional services and corporate workplaces. Therefore, this report calls for more research on the contexts of technology adoption in the Global South, and on women and minority groups, addressing their experience and focusing on sectors and industries that are currently under-researched.

Finally, the report calls for more women to be meaningfully involved in developing AI technologies and information and communication technologies (ICTs) more generally. Having more women lead AI design and development will be a significant, although still insufficient, step to more positive outcomes in technology integration. AI has enormous potential to help societies achieve their goals, but the equitable benefits of AI for workers and societies are not guaranteed and potential disadvantages are not equally shared either. While improving efficiency and productivity, AI can also deepen inequalities (OECD, 2019e; Sharma et al., 2020). The teams that develop technologies should draw on a diversity of backgrounds and experiences to ensure that stakeholder considerations are accounted for, and advocated to ensure that commercial or other drivers of AI do not override concerns for human rights including the right to equality and non-discrimination.

Key concept definitions



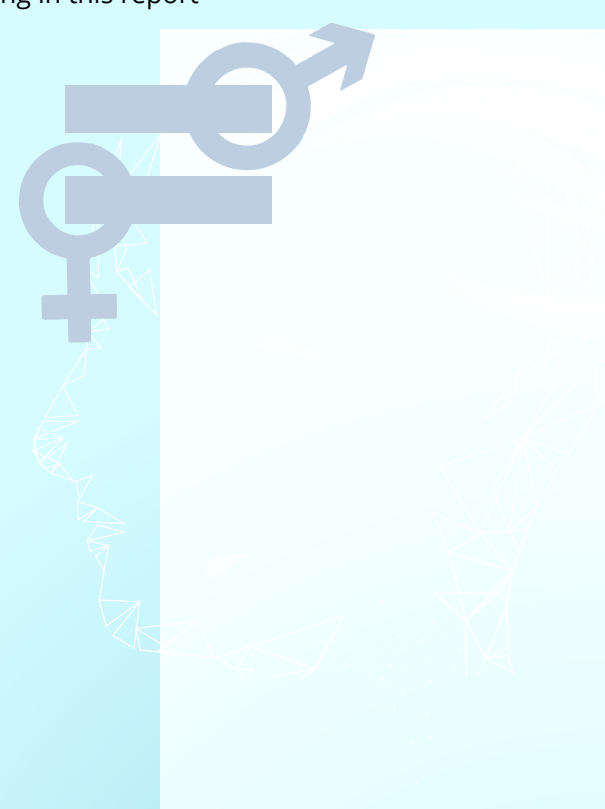
Artificial intelligence (AI): An AI system is “a machine-based system that is capable of influencing the environment by producing an output (predictions, recommendations or decisions) for a given set of objectives. It uses machine and/or human-based data and inputs to (i) perceive real and/or virtual environments; (ii) abstract these perceptions into models through analysis in an automated manner (e.g., with machine learning), or manually; and (iii) use model inference to formulate options for outcomes. AI systems are designed to operate with varying levels of autonomy” (OECD, 2019b). They comprise “machines capable of imitating certain functionalities of human intelligence, including such features as perception, learning, reasoning, problem solving, language interaction, and even producing creative work” (UNESCO, 2019b).

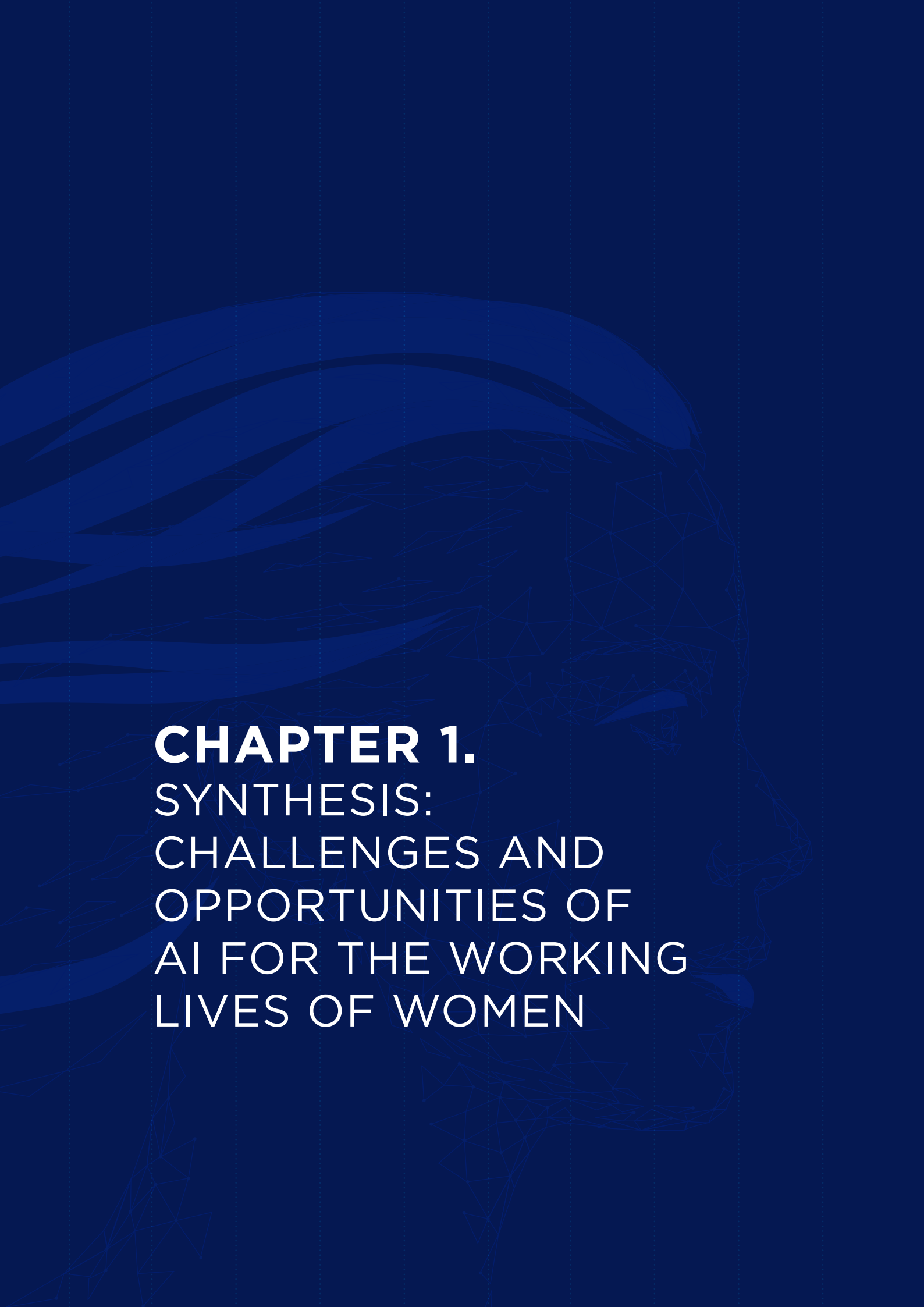


Labour market: Labour markets are where “workers exchange their labor power in return for wages, status, and other job rewards” and include consideration of social institutions and practices “that govern the purchase, sale, and pricing of labor services” such as how workers are “distributed among jobs, the rules that govern employment, mobility, the acquisition of skills and training, and the distribution of wages and other rewards” (Kalleberg & Sorensen, 1979). Broader “customs, rules, and relationships profoundly affect exchanges in the labor market” (Huffman, 2012).

Gender: According to UN Women, gender “refers to the social attributes and opportunities associated with being male and female and the relationships between women and men and girls and boys, as well as the relations between women and those between men. These attributes, opportunities and relationships are socially constructed and are learned through socialization processes. They are context/ time-specific and changeable. Gender determines what is expected, allowed and valued in a woman or a man in a given context. In most societies there are differences and inequalities between women and men in responsibilities assigned, activities undertaken, access to and control over resources, as well as decision-making opportunities. Gender is part of the broader socio-cultural context. Other important criteria for socio-cultural analysis include class, race, poverty level, ethnic group and age” (UN Women, 2022). Not all the organisations participating in this report define gender or define it in this manner.

Gender equality: According to UN Women, gender equality “refers to the equal rights, responsibilities and opportunities of women and men and girls and boys. Equality does not mean that women and men will become the same but that women’s and men’s rights, responsibilities and opportunities will not depend on whether they are born male or female. Gender equality implies that the interests, needs and priorities of both women and men are taken into consideration, recognizing the diversity of different groups of women and men. Gender equality is not a women’s issue but should concern and fully engage men as well as women. Equality between women and men is seen both as a human rights issue and as a precondition for, and indicator of, sustainable people-centered development” (UN Women, 2022). Not all the organisations participating in this report define gender equality or define it in this manner.





CHAPTER 1.
SYNTHESIS:
CHALLENGES AND
OPPORTUNITIES OF
AI FOR THE WORKING
LIVES OF WOMEN

CHAPTER 1.

SYNTHESIS: CHALLENGES AND OPPORTUNITIES OF AI FOR THE WORKING LIVES OF WOMEN

This chapter synthesises the challenges and opportunities in areas where artificial intelligence (AI) impacts the working lives of women – explored further in the other chapters of this report – with a focus on:



Access, connectivity and digital skills



Women in AI



Reskilling and upskilling



Gender stereotypes



Algorithmic transparency



Access, connectivity and digital skills

Challenges

Women lack connectivity to the internet and digital skills. Some of this comes from lack of education for women, or cultural/social norms that lead to women's exclusion from the digital world. Women and girls might struggle to access public ICT facilities due to unsafe roads or limits on their freedom of movement, or because the facilities are considered by some as unsuitable for women, or because women lack the financial independence to purchase digital technology or pay for internet connectivity (UNESCO, 2019a).

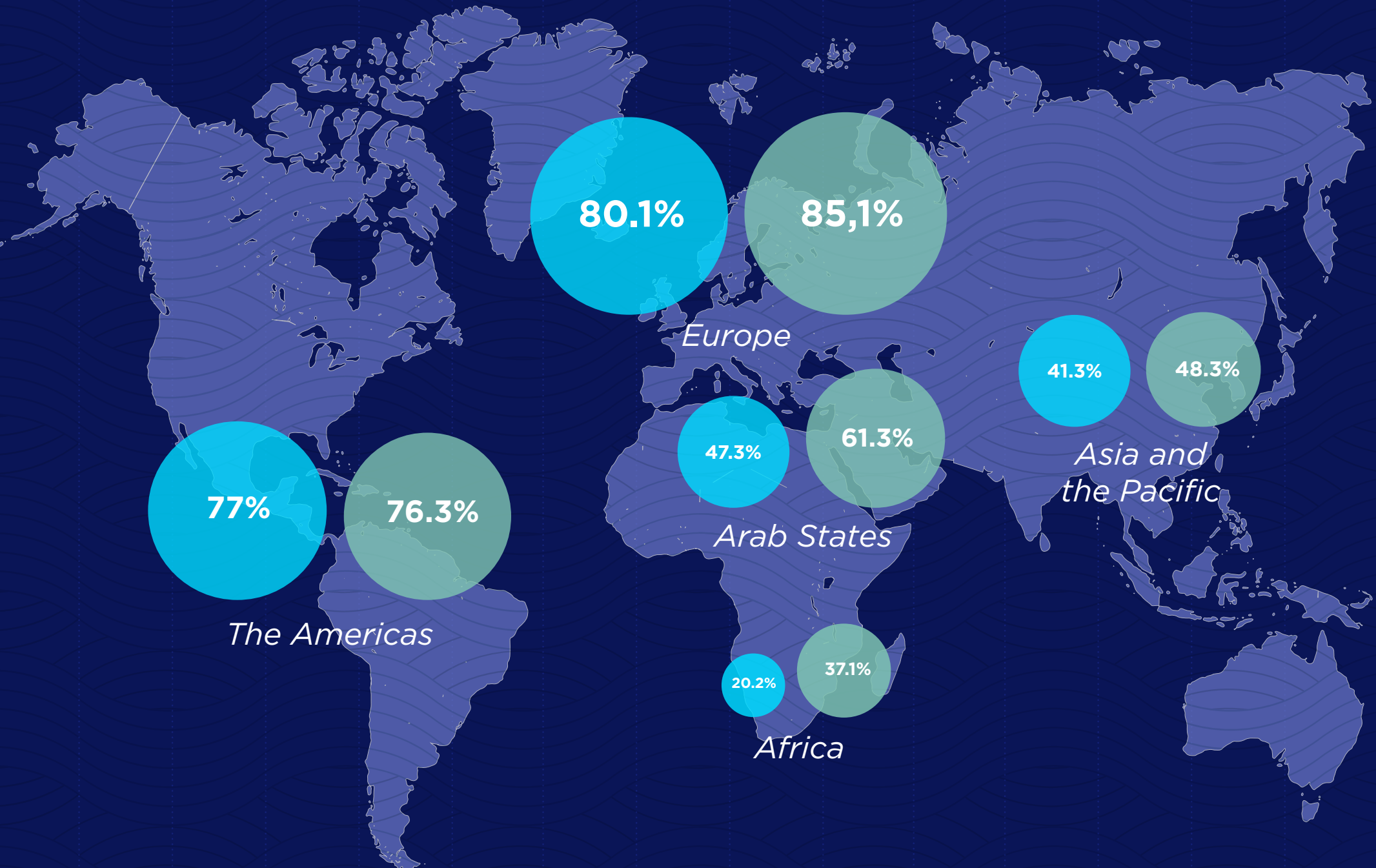
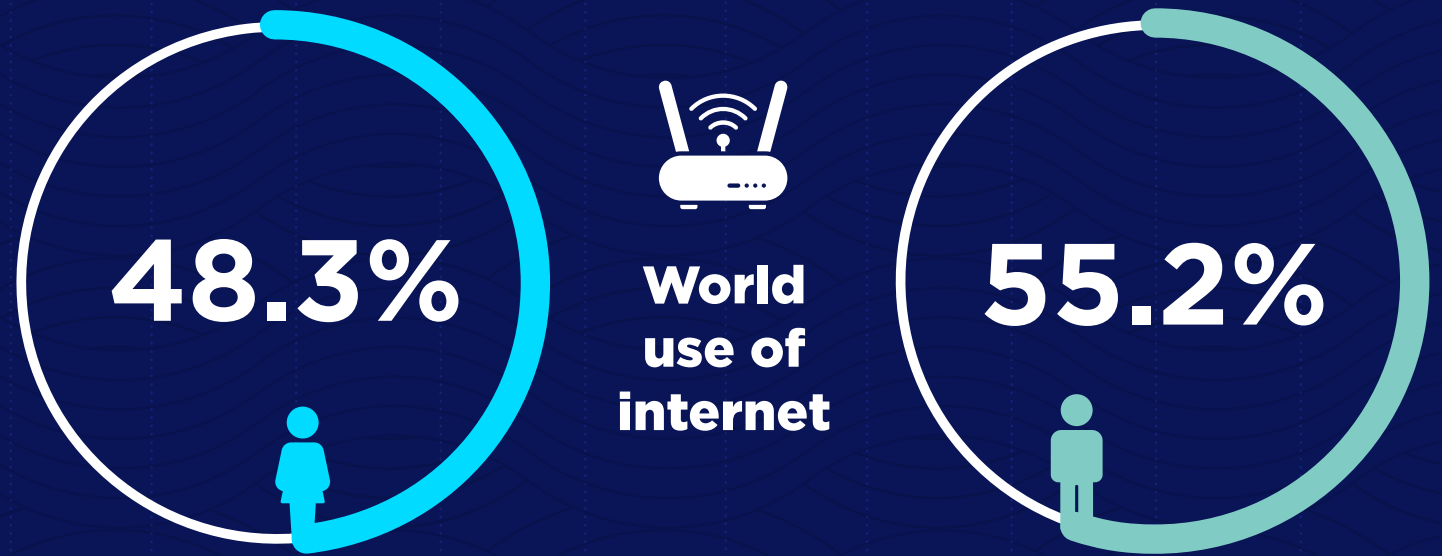
The weight of these issues differs internationally. The International Telecommunication Union (ITU) shows that women's and men's access to the internet differs around the world, with women in Africa having the lowest proportion of internet access (20.2%) compared to men (37.1%). The highest proportions are in Europe, where 80.1% of women and 85.1% of men have access to the internet.

In some instances, the lack of digital skills impedes people from accessing the internet. In Brazil, a lack of skills rather than the cost of access was found to be the primary reason why low-income groups do not use the internet, and in India, lack of skills and lack of perceived need for the internet were the primary limiting factors (UNESCO, 2019a).

The IDB outlines instances in selected Latin American countries (Bolivia, Colombia, El Salvador, Haiti, Mexico, Paraguay and Peru) where a high percentage of the population has smart phones or Internet access, but the user is not in a position to adopt a new habit of the effective use of technology (Urquidi & Ortega, 2020). The OECD found that women tend to use fewer services than men and are less confident about using the internet (OECD, 2018a).

Figure 1.1

Internet Use by Women and Men
Across the Globe in 2019
or latest available year



Sources: ITU, 2020a, 2020b, 2021c, 2021a, 2021d, 2021b

The gender gap in smartphone ownership results in roughly 327 million fewer women than men with a smartphone and mobile internet access (OECD, 2018a). According to the 2017 Global Findex Database, women in the Global South were less likely (37%) than men (43%) to have access to both a mobile phone and the internet (Demirgüç-Kunt et al., 2017). In a study across ten lower- and middle-income countries, women were 1.6 times more likely than men to report a lack of skills to be a barrier to internet use (WWWF, 2015).

The gendered divide in connectivity and digital skills lessens women's ability to (1) search for and apply for jobs, (2) secure a job and (3) thrive in an existing job, not to mention the opportunity to acquire knowledge and skills in preparation for possible employment. Digital technologies can often be lifelines for low-wage workers by connecting them to employers and work schedules through messaging apps (Ticona, 2022). However, women are less likely to have access to job platform sites. Research conducted across 25 countries found that women were 25% less likely than men to use the internet to search for a job (UNESCO, 2019a). UNESCO (2019a) also found that women and girls around the world are 25% less likely than men to know how to leverage digital technology for basic uses, such as using arithmetic formulas in a spreadsheet, and four times less likely to have computer programming skills.

Access to digital information is important to help women learn about, acquire and develop digital skills. The goal is not only to increase women's access to devices and the internet, but to complement it with digital skills that can facilitate their entry, permanence and growth in the labour market.

Gender gaps in access to ICTs vary in size and substance. For example, these are small in Latin America and the Caribbean compared to other Global South regions. In 2018, 63% of men and 57% of women in the region had internet access, while 83% of men and 80% of women had mobile phone access. However, when comparing regional averages to access gaps by country, large differences became apparent, mostly in favour of men. These vary from one percentage point in Chile, to 18 percentage points in Peru (Bustelo et al., 2019). Furthermore, men and women in the region differ in their uses of smartphones and the internet. While women tend to use technology primarily to communicate with others, men use it for productive and work-related activities. This is partly due to women feeling less prepared for new jobs and less familiar with how to generate income through digital platforms, which is related to a lack of digital skills (Petrie et al., 2021).

Opportunities

Closing the digital gender divide will present opportunities for the working lives of women. Digital skills can make a big difference for women's opportunities. UNESCO (2019a) describes how digital skills can open access to online markets to sell goods, enable women to start a business online, provide opportunities for career advancement and higher pay, or open access to loans and other financial services. In addition, digital skills can allow women to learn new skills related to their jobs, creating a virtuous cycle. Opportunities for women to develop digital skills and secure jobs brings opportunities to their community as well. Women tend to reinvest income into their families and communities at a higher rate than men (UNESCO, 2019a). The Alliance for Affordable Internet estimates that closing the digital gender gap represents a USD 524 billion opportunity for policymakers over the next five years (A4AI, 2021).

The OECD suggests that the internet, digital platforms, mobiles and digital financial services offer 'leapfrogging' opportunities that give women new possibilities to earn income, increase employment, and access knowledge and general information. Online or video-based upskilling and tutorials can help women make better use of digital tools and extract more value from them (OECD, 2018a). AI systems can also optimise job search services to

ensure that women receive equal opportunity when considering and applying for work. An IDB report, *Artificial Intelligence for Job Seeking* (2020), argues that correct and responsible use of information-intensive AI search has the potential to speed up services processes, customise them and potentially mitigate biases that lead to employment discrimination. With better and more sensitive design of the tools and algorithms to match the characteristics of vacancies with the skills of the candidate, AI tools for job searching could provide greater inclusion of vulnerable groups in the labour market (Urquidi & Ortega, 2020).

One opportunity lies in investing in initiatives, projects and companies that encourage women's access to digital devices and connectivity, and develop women's digital skills. With support, women around the world have a better chance of preparing for and searching for and securing jobs. For example, the EQUALS Global Partnership aims at narrowing the digital gender divide and fostering the digital skills of women and girls.

Initiatives like the IDB's fAIr LAC are also important for changing challenges into opportunities. fAIr LAC works with the private and public sectors, civil society and academia to promote the responsible use of AI to improve the delivery of social services and create development opportunities to reduce growing social inequalities. Their pilot projects and system experiments create models for ethical evaluation, as well as other tools for governments, entrepreneurs, and civil society to deepen their knowledge of the subject, provide guidelines and frameworks for responsible use of AI. These resources also consider how to influence policy and entrepreneurial ecosystems in Latin America and the Caribbean (LAC) countries (IDB, 2020).



Women in AI

Challenges

Too few women participate in AI-related jobs globally. This is a challenge for the future trajectory and development of AI systems. If systems are not developed by diverse teams, they will be less likely to cater to the needs of diverse users or align to human rights – for example, online gaming is often questioned for its gender bias and other discriminatory features. The OECD (2017) shows that differences in the careers of men and women workers originate early, while choosing their field of education. For example, at 15 years of age, an average of only 0.5% of girls across OECD countries aim to become ICT professionals, compared to 5% of boys. In science, technology, engineering and mathematics (STEM) fields, twice as many boys than girls expect to become engineers, scientists or architects.

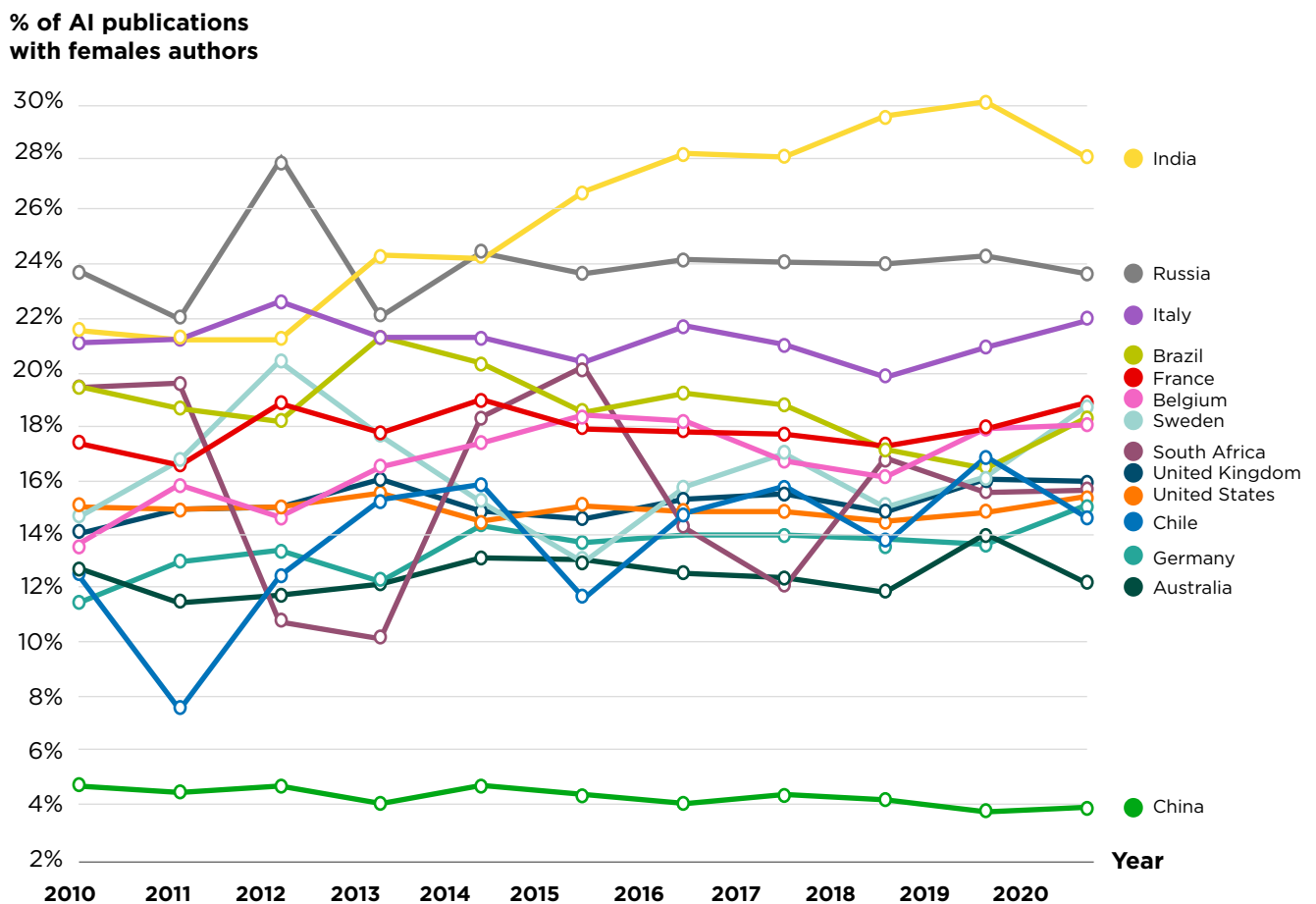
This trend is echoed among women in scientific research and development (R&D). UNESCO found that women make up 29.3% of science R&D positions globally, with the lowest proportions in Southwest Asia (18.5%), East Asia and the Pacific (23.9%). Women constitute less than one-third of the R&D workforce in sub-Saharan Africa (31.8%) as well as in North America and Western Europe (32.7%) (UNESCO, 2019c). And the situation seems to be deteriorating further. UNESCO (2019a) cite a 2018 European Commission study that shows that women's enrolment in ICT-related studies is declining in the EU since 2011 (Quirós et al., 2018). The authors note that similar declines have occurred throughout LAC and numerous high-income countries, including Australia, Korea and New Zealand (UNESCO, 2015), which shows that "[t]he digital space is becoming more male-dominated, not less so" (UNESCO, 2019a).

Among occupational employment data from G20 countries, the OECD found that the proportion of women ICT specialists ranged from 13% (Korea) to 32% (South Africa). They also estimated that just 7% of ICT patents in G20 countries are obtained by women, and only 10% of technology start-up companies seeking venture capital funding were founded by women (OECD, 2018a).

Gender disparity among authors who publish in the AI field is also evident. Studies have found that only 18% of authors at leading AI conferences are women (Mantha, 2019) and more than 80% of AI professors are men (Shoham et al., 2018). According to 2020 data on OECD.AI, women accounted for only 14% of authors of AI peer-reviewed articles worldwide. The OECD (2018a) notes that software is a male-dominated sector, especially at firms. One analysis of 'R', a well-known open-source software, showed that there are few women in the software world, that these women play less important roles, and that they are less connected to the network of software developers than their men colleagues (OECD, 2018a). Analysis of arXiv, an open-access repository of publications, shows that only an average 25.4% of publications addressing AI across 34 countries were co-authored by at least one woman. Among these, only three Latin American countries – Argentina (34%), Brazil (27%) and Mexico (27%) – ranked among those where gender differences in publications about AI are less pronounced (Gomez Mont et al., 2020).

Data from OECD.AI shows that the share of women credited in scientific publications in the Scopus database is below 20%. Among the countries listed in Figure 1.2, India seems to have the highest proportion of women in scientific publications on Scopus, at around 28%.

Figure 1.2. Share of women in scientific publications on Scopus



Source: OECD.AI, 2021

Increasing the number and rate of women in AI-related entrepreneurship and innovation will be key to making AI development inclusive and potentially driven by a multiplicity of enterprises, rather than the current landscape of a small number of dominant actors. The OECD notes that, while women's participation in inventive activities has increased, the pace is slow. Women's participation in patenting grew faster than patenting overall in 2004-15, and it grew in ICTs more than in other technological domains. But a low starting point coupled with relatively slow progress means that, at the current pace, women will not be involved in half of inventions patented with the five largest IP offices until 2080. Greater diversity of inventors is needed, especially to see emerging AI technologies consider the needs and rights of women and disadvantaged groups.

The gender gap must be bridged so that more women can participate in the AI workforce, including in terms of leadership in the design and development of AI. In 2019, women represented only 18% of C-Suite leaders among top AI start-ups around the globe (Best & Modi, 2019). Moreover, women with AI skills are less likely than men to be in senior roles (World Economic Forum, 2018).

This challenge is at the cutting-edge of AI development. Dr. Susan Leavy of University College Dublin argues that overrepresentation of men in the design of AI technologies could quietly undo decades of progress in gender equality. She develops the argument stating that machine intelligence learns primarily from observing data that it is presented with. This data is laden with stereotypical concepts of gender, thus she concludes the resulting application of the technology will perpetuate this bias. Women have a stake in building the digital economy to ensure that what the World Economic Forum brands as the Fourth Industrial Revolution¹ does not perpetuate gender bias (Bello et al., 2021).

There is an urgent need to increase the rate of women on AI, data science and software engineering teams and to educate men in the technology sector on gender bias, so that they can assess through a gender lens the data, design choices and societal context in which algorithmic decision making is used (Yarger et al., 2019). The lack of women in data science creates feedback loops that cause gender bias in AI and machine learning systems, according to a report by the UK's Alan Turing Institute, *Where are the women? Mapping the gender job gap in AI*. While women in data science and AI have higher formal education levels than men across all industries, the same report notes that women in the tech sector have higher turnover and attrition rates, and are more likely to occupy a job in the data and AI talent pool associated with lower status and pay, usually working within analytics, data preparation and exploration, rather than more prestigious jobs in engineering and machine learning (E. Young et al., 2021).

Opportunities

Demand for machine learning professionals is expected to increase 11% by 2024, according to the US Bureau of Labor Statistics (Keller, 2019). Organisations, governments and institutions should recognise this opportunity to expand quality work for women in the AI sector. Solutions include supporting STEM education, showcasing women AI trailblazers as role models, providing mentorship opportunities and addressing gender pay gaps in AI to bring more women into the sector and support their professional growth (Firth-Butterfield & Ammanath, 2021). The Girl Scouts of the USA participate in extracurricular education to increase interest, confidence and competence in STEM. The organisation pledged to add 2.5 million young women to the STEM workforce by 2025 and collaborate with industry leaders to prepare these women to be future STEM leaders (Firth-Butterfield & Ammanath, 2021).

¹ The Fourth Industrial Revolution refers to the changes that come with the rise of advances in robotics, artificial intelligence, the internet of things (IoT) and other systems that automate industrial or manufacturing practices.

UNESCO work in this area aims to :

- » **Improve the participation**, achievement and continuation of girls and women in STEM education and careers to reduce the gender gap in STEM professions;
- » **Strengthen the capacity** of countries to deliver gender-responsive STEM education, including through teacher training, educational contents and pedagogy; and
- » **Enhance awareness** of the importance of STEM education for girls and women. (UNESCO, 2017)

The need for more women to work in these sectors in the Global South is also crucial. Most AI experts are based in the Global North. However, many governments, for example in Africa, recognise the importance of training researchers and developers in AI. Initiatives have sprung up in the region to try to respond to the imbalance, such as Ghana's Women in Tech Africa, or Women in Machine Learning and African Girls Can Code (Bello et al., 2021; also see Mukhwana et al., 2020).

Some promising trends are emerging, as reported by Coursera (2021). Data from the Coursera Global Skills Report 2021 found that women are pursuing online education, including STEM courses, at a higher rate than before the COVID-19 pandemic. The share of course enrolments by women on Coursera increased from 38% in 2018-19 to 45% in 2020. For STEM courses, which teach high-demand digital skills, enrolment by women grew from 31% in 2018-19 to 38% in 2020. These increased participation rates continued in 2021, with 45% of overall course enrolments and 37% of STEM enrolments coming from women. Half of new registered learners on Coursera in 2021 were women, up from 45% in 2019. Women are also narrowing the gender gap in training for digital jobs, with enrolments in entry-level Professional Certificates increasing from 25% in 2019 to 37% in 2021.



Reskilling and upskilling

Challenges

The increased use of AI changes skill requirements within the workplace. First, it increases demand for digital skills to maintain and manage AI systems. Second, it increases demand for AI skills to create, develop, and engage with AI systems. Finally, it increases demand for human-only skills to work on the tasks for which AI systems are poorly suited. All of these changing skill requirements have adverse and differentiated impact on women as opposed to men.

First, women have less access than men to technology and the skills to use it, as explored above in the section on access, connectivity and digital skills.

Second, there is the challenge of inequality in AI skills, as addressed in the previous section. It is important to note that the ability to engage with and fully understand AI systems will be important for a broad range of professions, including those impacting AI policy and regulation, and also policies, laws and regulation surrounding economics, labour, education, trade, Intellectual Property and many other areas (Agrawal et al., 2019a).

Third, the ability to work on tasks that AI systems cannot perform reflects challenges to how the nature of jobs will change overall in the face of AI-driven automation. This implies changes in knowledge or practical skills that employees need to perform their jobs accurately and efficiently, and to social and soft skills that AI systems cannot currently perform (O'Connor, 2019).

For each of these changes, governments and policy makers should implement a comprehensive approach to addressing gender gaps in skills, career choices and employment outcomes (OECD, 2018a). Upskilling and reskilling of women needs to be considered in this context.

Opportunities

Reskilling and upskilling women to meet the increased demand for AI skills and digital literacy, and for women in STEM professions will be vital for women to adapt to jobs that transform, and to take advantage of ones that arise. Additionally, reskilling and upskilling will be important for changing the landscape of women's roles and leadership within workplaces.

There is opportunity here for multi-stakeholder and context-dependent action by governments, trade unions, organisations, technical communities, academia, IGOs and other stakeholders, and for international collaboration to ensure that the Global South is included. A McKinsey Global Institute (MGI) report examining six mature economies (Canada, France, Germany, Japan, the United Kingdom, and the United States) and four emerging economies (China, India, Mexico, and South Africa) argues that governments can contribute by providing women with subsidies to undertake training. Private sector actors also play a role, for instance by partnering with non-profits and universities to develop a broader pipeline of women going into jobs in tech fields (Madgavkar et al., 2019).

The UNESCO series on Internet Freedom acknowledges the importance of multi-stakeholder governance also in relation to AI. It says governance depends on co-operative mechanisms to develop trustworthy AI. The "goal of multi-stakeholder participation is to improve the inclusiveness and quality of decision-making by including all groups who have an interest in AI and its impact on wider social, economic and cultural development in open and transparent decision-making processes" (UNESCO, 2019b). Governments must engage with the issue according to their labour market, policies and skill mixes, and think about how to upskill and reskill women in response to the changes AI brings. In addition, organisations need to think about how they implement AI to create skill-equalising and skill-equalised work environments for women.

UNESCO and the Innovation for Policy Foundation (i4Policy) are currently developing a report on multi-stakeholder approaches to AI policy development. The document will help facilitate community consultations to advise governments on inclusive, multi-stakeholder-driven processes for the development of AI policies. Through a series of iterative learning and co-creation workshops, UNESCO and i4Policy will also develop a report on Activating Collective Intelligence for AI policy frameworks. The partnership will also leverage AI and innovation community networks worldwide to inform the development of global protocols on AI policy development processes, and offer use cases of multi-stakeholder approaches in diverse geographic regions for developing national AI strategies. The report will highlight that without participation of women, such processes are likely to be impoverished.

Reskilling and upskilling programmes should cover a range of skills. The OECD (2018a) points towards specific cognitive and non-cognitive skills, that are relevant to the digital skills needed in the age of AI:

- » basic literacy and reading
- » numeracy
- » information processing strategies, such as analysing, synthesising, integrating and interpreting relevant information from multiple texts and information sources
- » problem-solving

- » creative thinking
- » inter-personal skills
- » self-organisation
- » readiness to learn
- » management and communication

The OECD says all of these will be important to face the challenges and to grasp the opportunities of digital transformation, to work with the AI systems that emerge, and to capitalise on the skills these systems do not yet demonstrate but will stimulate in future (OECD, 2018a).

Other specific skills relate to AI development. [OECD.AI Live Data](#) shows the 10 fastest-growing AI skills in the labour supply of OECD countries annually from 2015 to 2020 (Figure 1.3), taken from LinkedIn member profiles. In 2020, these skills included Information Extraction, Data Structures, Pandas, PyTorch and Pattern Recognition.

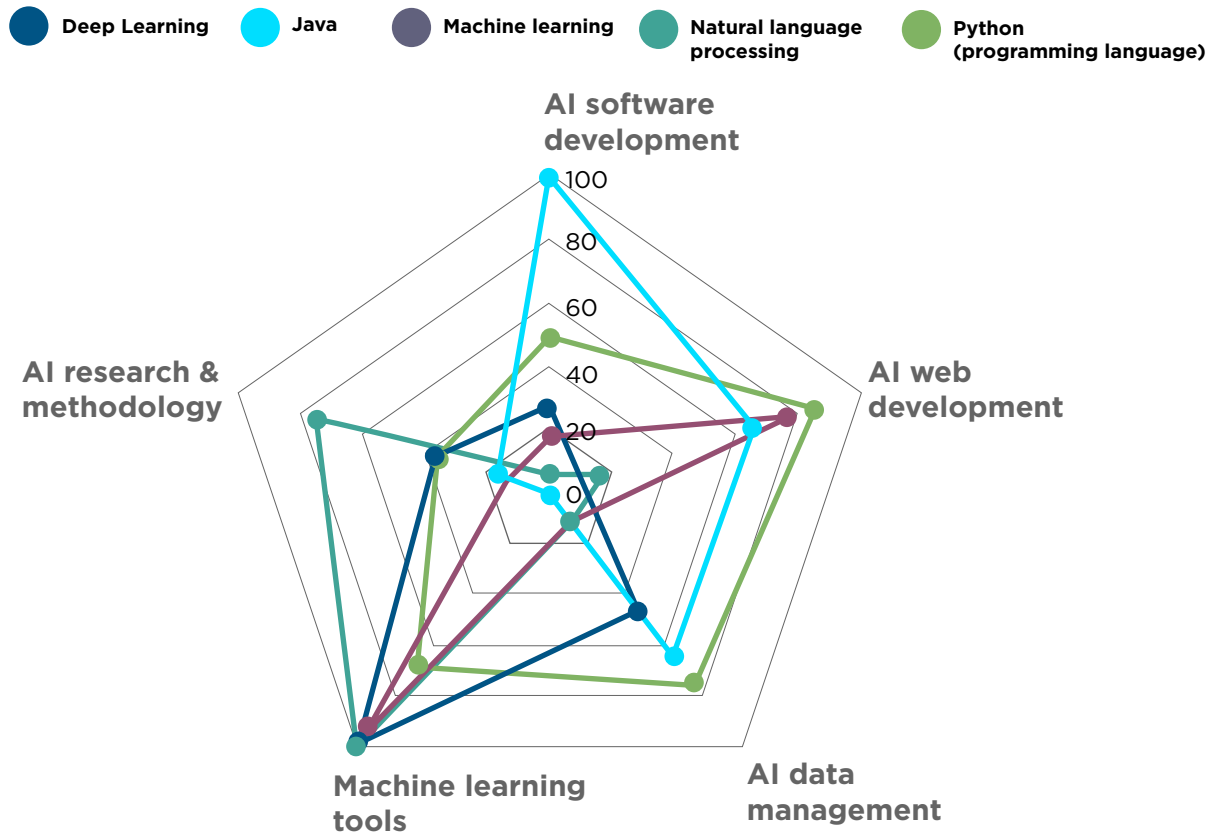
Figure 1.3 Fastest growing AI skills in OECD countries

| | 2016 | 2017 | 2018 | 2019 | 2020 |
|----|---------------------|------------------------|------------------------|-----------------------|------------------------------|
| 1 | Cognitive Computing | TensorFlow | CNNs | Pattern Recognition | Information Extraction |
| 2 | Deep Learning | Keras | MS Azure ML | Supervised Learning | Data Structures |
| 3 | Scikit-Learn | Alexa | PyTorch | Information Extration | Pandas |
| 4 | Association Rules | Deep Learning | Keras | CNNs | PyTorch |
| 5 | Web Mining | Pandas | Supervised Learning | Unsupervised Learning | Pattern Recognition |
| 6 | WordNet | CNNs | Pandas | Text Classification | Artificial Intelligence (AI) |
| 7 | Alexa | PyTorch | TensorFlow | Speech Recognition | Julia |
| 8 | IBM Watson | Scikit-Learn | Unsupervised Learning | PyTorch | Fuzzy Logic |
| 9 | Theano | Reinforcement Learning | Reinforcement Learning | Neural Networks | Artificial Neural Networks |
| 10 | Caffe | Supervised Learning | NLTK | Pandas | NLP |

Source: OECD.AI, 2021

In terms of AI skill demand, OECD.AI data show that, there five subcategories appear in job adverts regarding AI: software development; research and methodology; web development; machine learning tools; and data management. These subcategories in turn require AI skills including deep learning, machine learning, Python, text mining, Java and natural language processing. Figure 1.4 presents some of these skill requirements for different AI subcategories. More can be explored on the [OECD.AI Live Data website](#).

Figure 1.4 AI skill demand by subcategory



Source: OECD.AI, 2021

♀♂ Gender stereotypes

Challenges

AI systems can reinforce gender stereotypes, presenting major challenges for the working lives of women. This includes AI systems used in the workplace, government and rental spaces, etc, or at home. In domestic settings, AI systems might (1) rely on certain gendered stereotypes around care and assistance, and (2) create an unequal and unconstructive model of flexible working, which reinforces the narrative of women primarily doing care and domestic work.

In terms of the first challenge, some AI systems reinforce gendered stereotypes about care and assistance work. For example, the feminine voice of virtual personal assistants (VPAs) like Alexa and Siri can reinforce the stereotype that women are meant to care, assist and attend to the home, and to the needs of people in that home. This is evidence of how today's gender stereotypes can shape not only today's but also tomorrow's technologies, if status quo remains. There is a persistent gap between men and women in labour market participation due to childbirth and unequal distribution of responsibilities for child rearing. The IDB point out that the labour market participation gap reaches 40% points between men and women with children under five years old and that "one main challenge that women are still facing in the labour market is the cultural expectation of their role as principal caregivers".

After (re)entering the labour market, women, to a higher degree than men, participate in lower-quality and lower-paying jobs, which contributes to the gender wage gap (Bustelo et al., 2019). In most countries, childbirth and childcare take a large portion of new mothers out of the labour market, either temporarily or for a longer period, with direct impact on their opportunities, hours of work and earnings. While take up of part-time work in the

years after childbirth can prevent complete labour market withdrawal, it can represent a career trap for women, offering fewer professional transitions than men working part-time, which hampers upward mobility throughout their career (OECD, 2018b). Gender stereotypes replicated in technological systems pose a pernicious challenge in reinforcing these inequalities in work and care because they articulate out-of-date views in a high-tech vernacular.

AI systems can encourage flexible work arrangements by helping employers manage people working from home. Empowering women to manage their employed time through flexible working does not necessarily help change persistent stereotypes about domestic roles. Numerous studies on the impact of the COVID-19 pandemic found that women around the world spent more time than before on unpaid domestic and care work, which was already at a disproportionate level. During the pandemic women saw big increases in unpaid and caring responsibilities than their men counterparts (Borah Hazarika & Das, 2021; Craig & Churchill, 2021; Del Boca et al., 2020; Giurge et al., 2021; Hupkau & Petrongolo, 2020; Power, 2020; Sarker, 2021).

Women who spend more time on household work than men also have less time for reskilling and upskilling. Evidence from all countries examined by the Programme for the International Assessment of Adult Competencies shows that the share of women workers reporting family responsibilities as the main barrier to participating in education and training is always higher than that of by men (OECD, 2018a).

Gender norms about the division of household responsibilities continue to contribute to employment segregation by making women self-select into jobs and occupations that allow flexibility, or that build general skills more transferable to other firms if they resign in connection with childbirth. Unfortunately, these norms are very slow to change (Smita Das & Kotikula, 2019).

Opportunities

AI systems should take the existence of gender stereotypes into account and strive to change them. AI actors have an opportunity to change the way that AI systems mimic or interact with gender stereotypes. For example, AI systems should not associate women with care or assistance-related occupations in a biased manner. The narrative surrounding gender stereotypes could also be shifted, for instance by re-proposing AI-based flexible working as a tool to enable men to take up more domestic chores and parenting activities. The Bradesco case study in Chapter 4 shows a concrete way of how AI can even fight sexual harassment and men's violence against women.

Governments and organisations should review policies to ensure that AI brings equal benefits to all. Young et al. (2021) argue that, given that gendered roles in AI and data science is a global phenomenon, organisations must ensure the right human resources policies so that women and men have equal access to well-paid jobs and careers. Actionable incentives, targets and quotas for recruiting, upskilling, re-training, retaining and promoting women at work should be established, to support women's equal participation in 'frontier' technical and leadership roles.

The unequal distribution between men and women of domestic labour and care responsibilities also need to be more thoroughly considered in policy and implementation surrounding AI. Gendered norms surrounding care impact on the ability of women to reskill and upskill as training and learning also take time and require financial incentives and resources. For women, this can present a problem, especially if care responsibilities fall mainly upon them.

Policy strategies to foster gender equality exist, including :

- » Family-oriented policies to improve access to childcare facilities
- » Measures to encourage behavioural changes among both men and women, including combatting long hours, getting fathers more involved in caring, and promoting more equal forms of paid leave, and
- » Fostering changes in the workplace, including increase take-up of part-time and flexible working arrangements. (OECD, 2018b)

Technological innovation can help address inequalities related to stereotypes of women in both paid professional and unpaid domestic work. A 2019 report by the Institute for Women's Policy Research examined technological innovation as an opportunity to rethink the distribution of time spent on paid and unpaid work, tackle inequality in the division of domestic and care work between women and men, and provide time for the upskilling and lifelong learning needed to benefit from future opportunities (Hegewisch & Lacarte, 2019). Roberts et al. (2019) examine how automation could create a society of plenty, both financially and with more time for life outside the workplace, which could relieve many women of the 'double shift' of paid and unpaid work, and rebalance unpaid work between genders. However, this will not happen spontaneously: societies and governments need to realise the opportunity and manage the acceleration of digitalisation and automation, and involve in the leadership of this transformation those who could be most affected by it, including women.



Algorithmic transparency

Challenges

The lack of transparency in AI systems' functionality and outputs poses a challenge to understanding algorithmic biases and embedded discrimination: "[o]ne of the biggest obstacles to empirically characterising industry practices is the lack of publicly available information" (Raghavan et al., 2020). Scholars point out that 'black box' AI systems are the least likely to be challenged due to difficulty in interpreting their outcomes (Sanchez-Monedero et al., 2020).

Often, companies do not disclose how their systems work. For example, those that target or deliver employment ads to particular people do not disclose how they spread their budget or weigh it against relevance (Ali et al., 2019), making it hard to know when job seekers are affected and how to prevent discrimination (Wall & Schellmann, 2021). Datta et al. (2014) found that setting users' profile gender to 'Female' resulted in fewer instances of ads related to high-paying jobs, but they could not determine what caused those findings due to limited visibility into the ad ecosystem. They note that Google's policies to serve ads based on gender meant that one cannot be certain whether this outcome was intentional, even if it is discriminatory.

Opportunities

There is an opportunity for tech and software companies to be transparent about their AI systems with their users, researchers, government and their clients. Transparency is necessary to understand how systems work and why they produce certain outputs, and to carry out research to understand the current and potential impacts of AI systems on women. More transparency would facilitate the design and implementation of policies to limit the negative effects of specific systems on women in the workplace, at home and in society. By enabling both women and men to better understand AI systems and their outputs, algorithmic transparency could contribute to improving women's digital and AI skills, and to ensure gender-aware algorithms and related policies.

In May 2021, UNESCO initiated a global dialogue on the topic, outlining 26 high-level principles to enhance transparency of internet platform companies. These cover issues related to content and process, due diligence and redress, empowerment, commercial dimensions, personal data gathering and use, and data access. The principles' goal is to increase organisations' accountability, promote and protect human rights in the digital ecosystem, and strengthen freedom of expression and privacy that can inform both regulatory and self-regulatory policies (UNESCO, 2021a).

The OECD also highlights transparency and explainability as part of their AI Principles. It notes that AI actors should commit to transparency and responsible disclosure regarding AI systems, and provide meaningful, context-appropriate information to: foster understanding of the systems; make stakeholders aware of their interactions with AI systems; and enable those affected by AI to understand the outcome. In addition, it is important to enable those adversely affected by an AI system to challenge its outcome based on plain and easy-to-understand information on the factors and logic that served as the basis for a prediction, recommendation or decision (OECD, 2020).



CHAPTER 2. CHANGES IN SKILLS REQUIREMENTS DRIVEN BY AI

CHAPTER 2.

CHANGES IN SKILLS REQUIREMENTS DRIVEN BY AI

The introduction of artificial intelligence (AI) technologies in workplaces is shifting the types of skills workers need. These technologies are used to automate employee tasks, particularly those that are routine or repetitive. The rationale from a commercial standpoint would be that where savings in wage bills can be achieved, productivity gains can be achieved with impact on profit levels. One key difference between AI-driven automation and automation in general is that AI technologies can automate more complex tasks that usually require human administration. Further, AI can be used to automate non-routine tasks of highly skilled workers. Therefore, jobs that once seemed beyond the scope of automation are now more commonly automated using AI systems (Georgieff & Hye, 2021).

New technologies can lead to the creation of new tasks and occupations, and researchers are working to map the overall balance of those effects from AI technologies (Bosch et al., 2019). While the evidence remains mixed, it supports the idea that AI could have a positive effect on employment through job creation. Two-thirds of 300 tech executives responding to the 2019 Edelman AI Survey believed that AI could increase employment (Edelman, 2019). Many businesses predict that AI will shift work from some occupations to others, rather than eliminate or reduce overall labour demand (Bessen, 2019). Empirical evidence from the OECD over the last ten years supports the view that there will not likely be an overall decline in employment and wages in occupations exposed to AI (Lane & Saint-Martin, 2021). However, despite a potential increase in opportunities, emerging economies are likely to face significantly more challenges related to rapid technological progress (Soto, 2020).

This chapter discusses AI-driven automation and the changing skill requirements that come with AI implementation, and focuses on how these changes might impact women at work. The introduction of AI technologies could determine which workers remain or transition to other equally or better paid jobs depending on what shapes economies in the future (Roberts et al., 2019). If the adoption of AI technology is not done prudently, it risks widening gender gaps in the workforce (Ripani et al., 2017).

AI-driven automation

Tasks and AI-driven automation

The nature of tasks within jobs is important when thinking about which jobs will be impacted by AI technologies. New technologies can replace certain tasks that people do and thus change the skills workplaces require. Further, new technologies can enhance how people complete specific tasks. AI-driven automation is distinct from traditional automation in that it can carry out more complex tasks. This makes AI systems more prone to replace highly skilled, non-routine jobs (Georgieff & Hye, 2021). AI systems often carry out specific and limited tasks within the workplace. Box 2.1 outlines the seven categories of tasks commonly performed by AI systems.

Box 2.1. Tasks commonly performed by AI systems

The 'task' of an AI system refers to the function it performs. The following categories cover most tasks performed by AI systems:

- » **Recognition:** Identifying and categorising data (e.g., image, video, audio and text) into specific classifications.
- » **Event detection:** Connecting data points to detect patterns, and outliers or anomalies.
- » **Forecasting:** Using previous and existing behaviours to predict future outcomes.
- » **Personalisation:** Developing a profile of an individual, and learning and adapting its output to that individual over time.
- » **Interaction support:** Interpreting and creating content to power conversational and other interactions between machines and humans (possibly involving multiple media, such as voice, text, and images).
- » **Goal-driven optimisation:** Finding the optimal solution to a problem for a cost function or predefined goal.
- » **Reasoning with knowledge structures:** Inferring new possible outcomes through modelling and simulation even if they are not present in existing data.

Source: (OECD, 2021c)

When it comes to automation generally, routine tasks are often assumed to be those most likely to be replaced. Studies predict that jobs in logistics, administrative support or data processing are liable to be automated (Agar et al., 2018; Frey & Osborne, 2017). This supports the idea that the least automatable tasks rely on humans' ability to process complexity, their emotional intelligence, deep thoughtfulness and situational navigation. One study argues that the three occupations at the lowest risk of automation are medical practitioners, higher-education teachers and senior professionals of educational establishments, which are all considered highly skilled (ONS, 2019) and which arguably require emotional and contextual assessment. Therefore, some could argue that AI favours highly educated workers in jobs less likely to be automated because they entail a high proportion of tasks involving expertise and social interactions (Agar et al., 2018). However, as AI systems become more effective and accurate, non-routine tasks and jobs that once seemed 'safe' from automation are exposed to automation through AI systems (Georgieff & Hye, 2021).

AI-driven automation can replace numerous cognitive tasks performed by humans. Research suggests that AI systems will be able to perform forecasting tasks in many contexts, using prediction technology and data to model a future outcome. Machine learning – a branch of AI that leverages statistical approaches to learn from historical data and make predictions in new situations – identifies patterns and uses data to fill in missing information through inferences. While people in certain jobs rely on prediction skills, for example when screening resumes (Agrawal et al., 2019b), prediction is only one input into decision-making. People make decisions within a context: teachers decide how to educate, and managers decide whom to recruit based on a variety of changing factors. As technologies get better at forecasting, for any given worker, "a key predictor of whether AI will substitute for their job is the degree to which the core skill they bring to the job involves prediction" (Agrawal et al., 2019b).

The impact of AI-driven automation on the work of women

What does the potential of AI-driven automation mean for work performed by women? Research gives no clear answer.

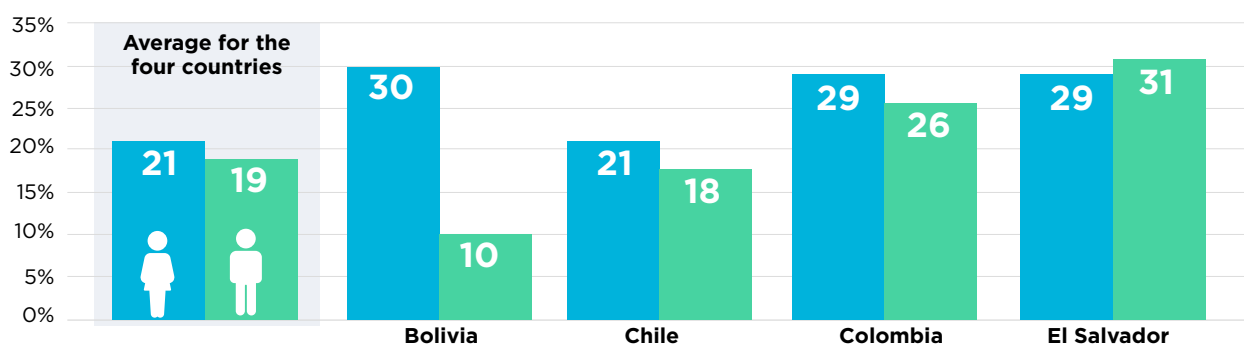
Studies estimate that occupations with predominantly men workers are more exposed to the risks of automation because women more likely work in roles requiring interpersonal skills, potentially less in danger of being replaced by AI systems (OECD, 2017a; Webb, 2019). This could mean that tasks requiring so-called ‘soft-skills’, including tasks not easily done by AI systems, would be more in demand. Traditionally, such soft-skill work is associated with women as, for example, women are more highly represented in care-related occupations (Allas et al., 2019). This could put women in a better position when it comes to avoiding the detrimental impact of AI-driven automation (O’Connor, 2019; Rust & Huang, 2021).

Others point out that women are more prevalent than men in occupations such as clerical support and service worker jobs with high automation potential due to a high share of routine cognitive tasks. This would leave women’s jobs more exposed to being replaced by AI technology (Madgavkar et al., 2019; Servoz, 2019). One study in the US, found women to be overrepresented in administrative jobs – 70% of the clerical and administrative workforce in the US – whose automation potential through AI has been estimated to stand at 60% in the country (Muro et al., 2019). While jobs with a higher proportion of tasks that involve more complexity, such as managing people, applying expertise, social interactions, emotional intelligence, or contextual assessment, might be at lower risk of AI-driven automation, gender inequalities have resulted in women being underrepresented in managerial positions. In financial services, women represent almost 50% of the total workforce, but hold only 25% of senior-management positions. If managerial positions are relatively more insulated from the shocks of automation, and clerical and administrative jobs face more risks, women in the financial services sector will overall be disproportionately affected by AI-based automation (Gallego et al., 2019).

This inability to predict a single future effect of AI on women’s employment indicates that AI-driven automation is often context-dependent and influenced by an individual’s social, economic and cultural standing. These vary by country or region: the power women have within the labour force varies with differing social and political contexts, and how these relate to corporate governance. Because women’s exposure to the risks of automation are not the same around the world, neither are the ways to mitigate them.

The IDB report, *The Future of Work in Latin America and the Caribbean (LAC)*, analyses data from four countries in Latin America to show how the risk of automation, including AI based automation, differs across countries (Figure 2.1). In Bolivia, 30% of women are at high risk of having their jobs automated compared to 10% of men. The risks of automation in El Salvador, by comparison, are roughly equal (29% of women versus 31% of men), also the case in Colombia and Chile.

Figure 2.1 Risk of automation by gender in select LAC countries



Source: Bustelo et al., 2019.

Note: Proportion of worker whose automation risk is greater than 70%. For the estimates, the samples of urban employed persons between 18 and 60 years, excluding the agricultural, forestry, fisheries and mining sectors, is taken into account. The difference between men and women is statistically significant at 5% or less. Calculations based on STEP 2012 and 2013 (Bolivia, Colombia and El Salvador) and P1AAC 2014 survey (Chile). Source et al. (2019b)

In addition to automation, the rise of online job platforms that use AI, which accelerated during the COVID-19 pandemic, is also transforming the working lives of women. Online job platforms can change where work happens and can expose men and women to the risks of AI-based automation differently. For instance, MTurk, a crowdsourcing tool owned by Amazon, allows businesses to outsource their work by hiring remotely located workers to perform tasks. The platform was designed to hire workers for routine tasks that computers cannot do. This type of work, known as the “gig economy”, is defined by short-term contracts or freelance work rather than permanent jobs, thus without access to social security or health insurance for workers. Gig economy jobs often leave women in a vulnerable position, especially in the Global South (Albrieu, 2021). Approximately 57% of people on Mturk identify in their profiles as ‘Female’ (Moss & Litman, 2020). Many AI systems used in web search, images categorisation and social media content moderation rely on the “ghost work” of people on platforms like Mturk – “people and software working together to deliver seemingly automated services to customers” (Gray & Suri, 2019).

Box 2.2 The Fairwork Project

[The Fairwork Project](#), based at the Oxford Internet Institute and the WZB Berlin Social Science Center, evaluates working conditions of digital platforms in 20 countries across five continents and ranks them based on five principles of fair work. Germany’s Federal Ministry for Economic Cooperation and Development commissioned GIZ, the country’s international development agency, to run a project on [Digitisation and employment: Shaping the future of work](#), focused on partner countries India and Rwanda. The project aims to identify and analyse trends and developments to harness the potential for more and better jobs, facilitate integration into global value chains, and mitigate negative impacts at an early stage. Projects like this show how academia and government can collaborate to map the changes underway in working conditions, and particularly these changes’ impact on women around the globe.

In some contexts, economic restrictions or lack of access to technology (or even electricity) slow the adoption of AI and change its impacts on work (Frey & Osborne, 2013). An OECD study found that, in many cases, while jobs are theoretically automatable through AI, they are not likely to be in the Global South because slower technological adoption makes this not yet feasible (Soto, 2020). In Latin America, factors like the low level of workforce preparedness, the low cost of labour, the prevalence of small and medium-sized companies, fragile infrastructure and scarcer access to credit markets can slow technological changes (Bosch et al., 2019). Slower technological adoption can both deprive these countries of productivity gains and worsen gender inequalities in the labour market. However, in some cases, the adoption of AI-driven automation might have positive impacts on employees and enhance workplace productivity, as discussed in the case study below.



Case study:

Harnessing the power of AI for women in African agriculture

Women account for 50% of the workforce in agriculture in most eastern and southern African countries (Dugbazah et al., 2021). Around 62% of women across Africa are involved in farming, and in producing, processing and marketing food (Kamau-Rutenberg, 2018). Despite these high participation rates, significant gender inequalities in agriculture remain, including in productivity and compensation (Dugbazah et al., 2021; FAO, 2011; Rodgers & Akram-Lodhi, 2018; UN Women, 2015). Gender gaps in agricultural productivity arise because women have inequitable access to agricultural inputs, including land, family labour, high-yield crops, machinery, pesticides and fertiliser. Women also receive lower prices for their crop output and have less access to markets. Women's lower education levels in combination with them having to shoulder the major part, if not all, of childcare responsibilities, make these inequalities worse (Peterman et al., 2010; UN Women, 2015).

Across Africa, farmers are beginning to gather and analyse information about their crops using digital technologies and data. This includes mapping gardens and fields to get support from technical experts, searching for market information and prices, and supporting tasks of getting crops to market, including transporting, marketing and sales, and digital payments (Dugbazah et al., 2021). For example, in Kenya, farmers use smartphones to access weather information and predict suitable times for planting and harvesting.

AI can play a positive role in reducing gender inequalities in African agriculture. The African Union Panel on Innovation and Emerging Technologies (APET) encourages African countries to incorporate these innovations in addressing the gender gap. The New Partnership for Africa's Development (NEPAD) says that emerging technologies such as digital, AI and robotics can improve agricultural processing.

Buy from Women, a platform set up by UN Women, connects women farmers to information, financing and markets using an open-source, end-to-end, cloud-based and mobile-enabled supply chain system. The information captured through the platform can unlock both traditional and innovative financing for farmers and cooperatives to invest in processing and post-harvesting labour, and time-saving equipment. This enables farmers to avoid distress selling, receive higher prices and reduce post-harvest losses. In Rwanda, farmers use Buy from Women to predict production levels and crop yields. By mapping new users' land plots upon registration, the platform helps generate a yield forecast, which helps with planning. The platform also helps small farmers connect to agricultural supply chains, providing them with information on market prices. The program includes support for women on gender equality issues and provides new business opportunities (UN Women, 2016).²

There are also women-led projects in Africa aiming to harness the power of AI for women's economic empowerment. Fatoumata Thiam, a Ph.D. student at Gaston Berger University in Senegal, is developing an automated irrigation system that

² There are also interesting examples outside Africa of AI-enabled apps helping farmers track their crops and market conditions. For example, Microsoft and the International Crop Research Institute for Semi-Arid Tropics (ICRISAT) developed the AI Sowing App to support thousands of farmers in India. The app sends data-enabled sowing advisories using text-based phones and does not require sensors or additional expenses (Microsoft, 2017). Plantix, developed by a German start-up, is another example of an app powered by deep neural networks that helps farmers distinguish between and diagnose plant diseases, pests or nutrient deficiencies.

will compute the right amount of water for overall crop growth, ensuring only the required water is supplied. The goal is to propose an AI-based solution that will optimise and automate irrigation in the Niayes area in north-western Senegal (Thiam, 2021).

How AI might impact women working in agriculture across Africa is a complex question with each country presenting unique opportunities and challenges. According to Yana Rodgers, Professor of Labour Studies and Employment Relations at Rutgers University, USA, who studies the cost of the gender gap in African agricultural productivity, “more research is needed on the augmentation effect of new technology and the collaboration between humans and robotics given the strong complementarities that exist between automation and labour”.

However, the benefits of AI adoption in agriculture for women in Africa are not always equally spread. Professor Haroon Akram-Lodhi at Trent University, Canada, urges caution about generalising from the benefits of AI in agricultural settings. While there is potential for women to benefit from the use of AI in agriculture, the adoption of AI systems is commonly tied to resources to spend on this adoption. This means that those in a better financial position i.e. mainly men, are best placed to adopt the technology, implying that AI adoption will worsen existing gender inequalities in agriculture. Financial and banking gaps make matters worse: in sub-Saharan Africa, only 37% of women have bank accounts, compared to approximately 48% of men (Dugbazah et al., 2021).

Other obstacles exist. According to Professor Akram-Lodhi, a “heavily gendered pattern of production, particularly with farms jointly managed by spouses” means that men might “wield these technologies for their own benefit”. Experience with efforts to turn crops cultivated by women into cash crops suggests that if there were “efforts sought to enhance women’s access to such technologies men would find strategies to usurp the benefits”.

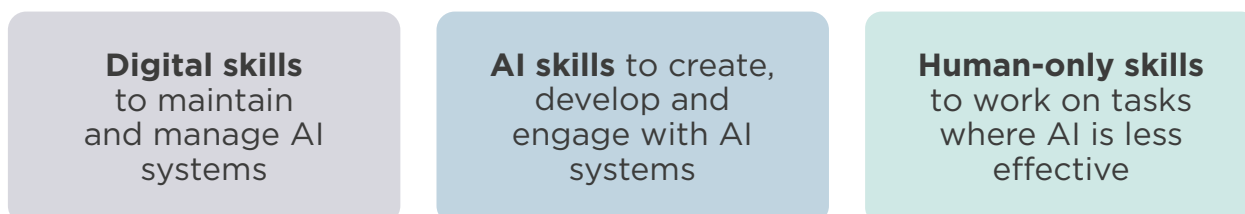
Women in African agriculture do not shape research agendas, set priorities or play leading roles in decision-making in agricultural research and development. Women account for just 22% of agricultural scientists in Africa (Kamau-Rutenberg, 2018). However, initiatives like African Women in Agricultural Research Development (AWARD) work to promote inclusive agriculture by training women to lead critical advances in agricultural research and innovation. Their AWARD Fellowship initiative has strengthened the science, leadership and mentoring skills of 1158 scientists from over 300 research institutions in 16 African countries (Kamau-Rutenberg, 2018).

Equalising African agriculture for women could be beneficial socially and economically. While findings suggest significant returns on investment in empowering women in agriculture, there are few estimates of these (C. L. Anderson et al., 2021). However, empirical evidence across Africa suggests that if women had access to the same agricultural inputs as men, they could increase their yields by 20-30%, which could bring millions of people out of hunger (FAO, 2011).

While there are steps in the right direction to ensure that AI tools and technologies in African agriculture do not worsen gender inequalities, bias embedded in national governance structures such as laws, regulatory systems and policy frameworks – such as limiting women’s right to own land – impacts whether women farmers will reap the benefits. Getting more women into leadership and decision-making positions, however, could lead to legal and policy changes on the continent.

The effect of AI on skill requirements

The adoption of AI technologies changes what job skills are in demand. Certain of these can be taught, such as working with computers or advanced numeracy, while others are less tangible, such as empathy, creativity and emotional intelligence.³ Therefore, AI-driven automation can create new opportunities for work. For example, AI technologies can shift workers away from repetitive and time-consuming tasks towards more productive and engaging tasks (Georgieff & Hye, 2021). This section discusses the effect of AI on women's skill requirements in relation to three AI-induced shifts:



These three types of skills recognise how technology changes can shape the demand for skills. Emerging AI systems will require more people who can design, work within or support these systems. These types of jobs will represent an opportunity for women who have AI or digital literacy skills and education in STEM fields.

Digital skills: Maintaining and managing AI systems

The introduction of AI will lead to an increase in the demand for digital skills (OECD, 2016). UNESCO defines digital skills as “the ability to access, manage, understand, integrate, communicate, evaluate and create information safely and appropriately through digital devices and networked technologies for participation in economic and social life” (UNESCO, 2019a). Some of these draw on wider media and information literacy and ethical reflection competencies.

Teams will need to manage, maintain and work closely with AI systems (OECD, 2018a; Roberts et al., 2019). Digital skills will also be important for workers to understand the systems being implemented and raise concerns or objections where they feel necessary. Therefore, the ability of women to adapt to technological innovation in AI systems will be crucial for them to thrive at work. Moreover, these skills will be important for women to rise through the ranks in digital or tech-oriented organisations. Data from the OECD Survey of Adult Skills – conducted as part of the Programme for the International Assessment of Adult Competencies (PIAAC) – shows that most skilled occupations, such as managers and professionals, exhibit more intensive use of ICT's than less skilled occupations (OECD, 2018a). Another recent report from the OECD finds that workers with good digital skills might find it easier to use AI effectively and shift to non-automatable, higher-value-added tasks within their occupations. The report also finds that the opposite may be true for workers with poor digital skills, who may not be able to interact efficiently with AI and thus not reap potential benefits of the technology (Georgieff & Hye, 2021).

However, research shows that women tend to lag behind men when it comes to ICT skills and digital literacy. There is an undeniable and growing gender-related digital skills gap (Quirós et al., 2018). UNESCO estimated in 2019 that women globally were an average of 25% less likely than men to know how to use ICT for basic purposes such as simple arithmetic formulas in a spreadsheet. This gap was greater for older, less educated and poorer women, and those in rural areas. More troublingly, the gap seems to be growing, at least in high-income countries (UNESCO, 2019a).

³ According to OECD definitions “Skills are the ability and capacity to carry out processes and be able to use one's knowledge in a responsible way to achieve a goal. Skills are part of a holistic concept of competency, involving the mobilisation of knowledge, skills, attitudes and values to meet complex demands” (OECD, 2019a).

The OECD has found similar results as part of a 2018 report on Bridging the Digital Gender Divide. According to the report, when skills including problem-solving in technology-rich environments, as well as literacy and numeracy are considered working women in most OECD countries are less likely than men to be high performers or have a well-rounded mix of skills. Further, the gender gap among high performing countries is particularly wide in countries like Austria, Japan and Norway. On the other hand, the proportion of workers lacking basic skills is similar between genders in economies such as Singapore and the Russian Federation. However in the case of Singapore, fewer women than men have well-rounded skill sets (OECD, 2018a, 2019c). In most OECD countries listed in the report, older working women (aged between 55 and 64 years) are more likely than men in the same age group to lack basic skills in literacy, numeracy and problem-solving in technology-rich environments, which are foundational for continued learning. Training and learning also take time and require financial incentives and resources. For women this can represent a problem, especially if family responsibilities fall disproportionately upon them (OECD, 2018a).

Lower levels of digital literacy for women are linked to women being less likely to have access to a mobile device and the internet (Bello et al., 2021; OECD, 2018a; UNESCO, 2019a). Cultural, economic or social reasons could be the reason why women have less access to public ICT facilities due to unsafe roads, limits on their freedom of movement, such facilities being considered unsuitable for women, or women not having the financial independence to purchase digital technology or pay for internet connectivity (UNESCO, 2019a).

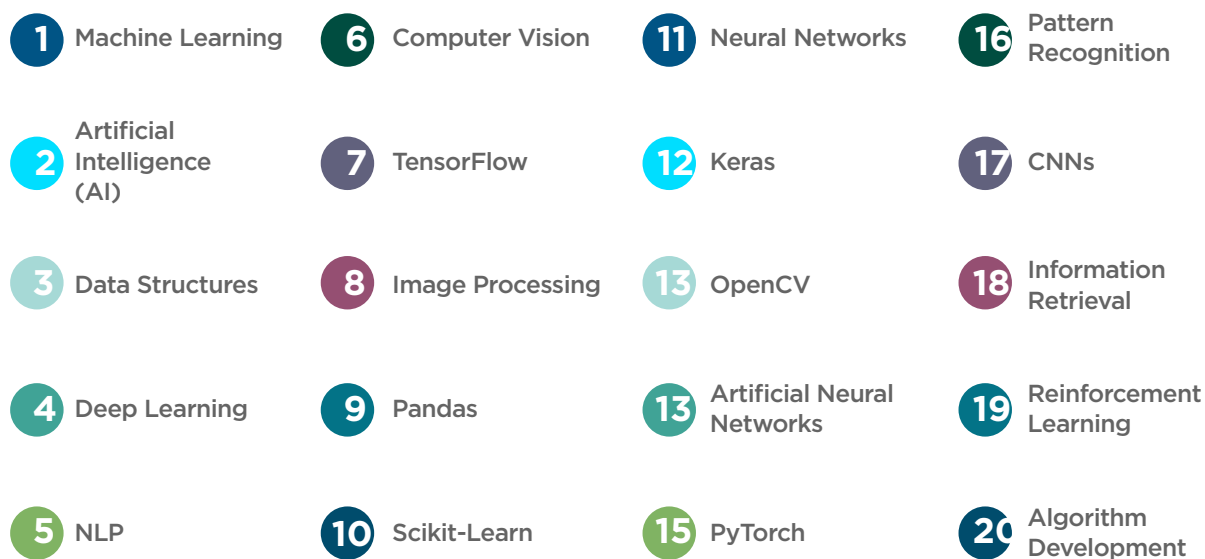
In response, the IDB launched the 21st Century Skills initiative, aiming to gather and organise stakeholders from public and private sectors to provide citizens with transversal or foundational skills. The definition of transversal skills can fluctuate but comprises skills described as essential to human development, which are reusable and transferable from one field to another, and not related to a specific job, task, field, discipline or occupation.

Going forward, it will be essential to ensure that women are equipped through reskilling and upskilling to meet the requirements of the future labour market. According to the OECD, helping people navigate the changing world of work means helping them acquire the skills for new jobs and new tasks (OECD, 2021b) because, depending on the nature of the job, a worker's job may be enhanced by, or be in competition with, AI (Frank et al., 2019).

The OECD AI Principles recommend building human capacity and preparing for labour market transformations, and specify that "governments should work closely with stakeholders to prepare for the transformation of the world of work and of society. They should empower people to effectively use and interact with AI systems across a breadth of applications, including by equipping them with the necessary skills". Ensuring a fair transition for workers as AI is deployed should include training programmes, support for displacement and access to new opportunities in the labour market, as well as the responsible use of AI at work to ensure the benefits from AI are shared broadly and fairly (OECD, 2020).

AI skills: Creating, developing, and engaging with AI systems

The second change in the labour market stemming from the introduction of AI is increased demand for workers with AI skills specifically. AI skills allow people to create and develop, engage with and understand AI systems. Figure 2.2 shows the OECD measurement of the 20 most prevalent AI skills among LinkedIn users worldwide from 2015 to 2020. AI skills include machine learning, deep learning, natural language processing (NLP) and many more.

Figure 2.2 Most prevalent AI skills worldwide

Source: OECD.AI, 2021

However, a gender divide in AI skills exists globally, and this divide starts in the early stages of career development. Women are less likely to pursue ICT studies and constitute less than a third of those enrolling in university level ICT studies – the biggest gender disparity among all disciplines (UNESCO, 2019a). Women are also significantly underrepresented in STEM education. Estimates suggest that women currently hold 56% of university degrees overall, but just 36% of STEM degrees and make up only 25% of the STEM workforce (Gallego et al., 2019).

The OECD Programme for International Student Assessment (PISA) revealed a gender gap in career expectations. The OECD found that in 2018, across 63 countries, fewer than 2% of girls had plans to become engineers (Mann et al., 2020). The World Bank has found that boys are more likely to specialise in well-paid STEM fields, apparently influenced by teachers and parents, knowledge of salaries in a field, and self-confidence (Smita Das & Kotikula, 2019).

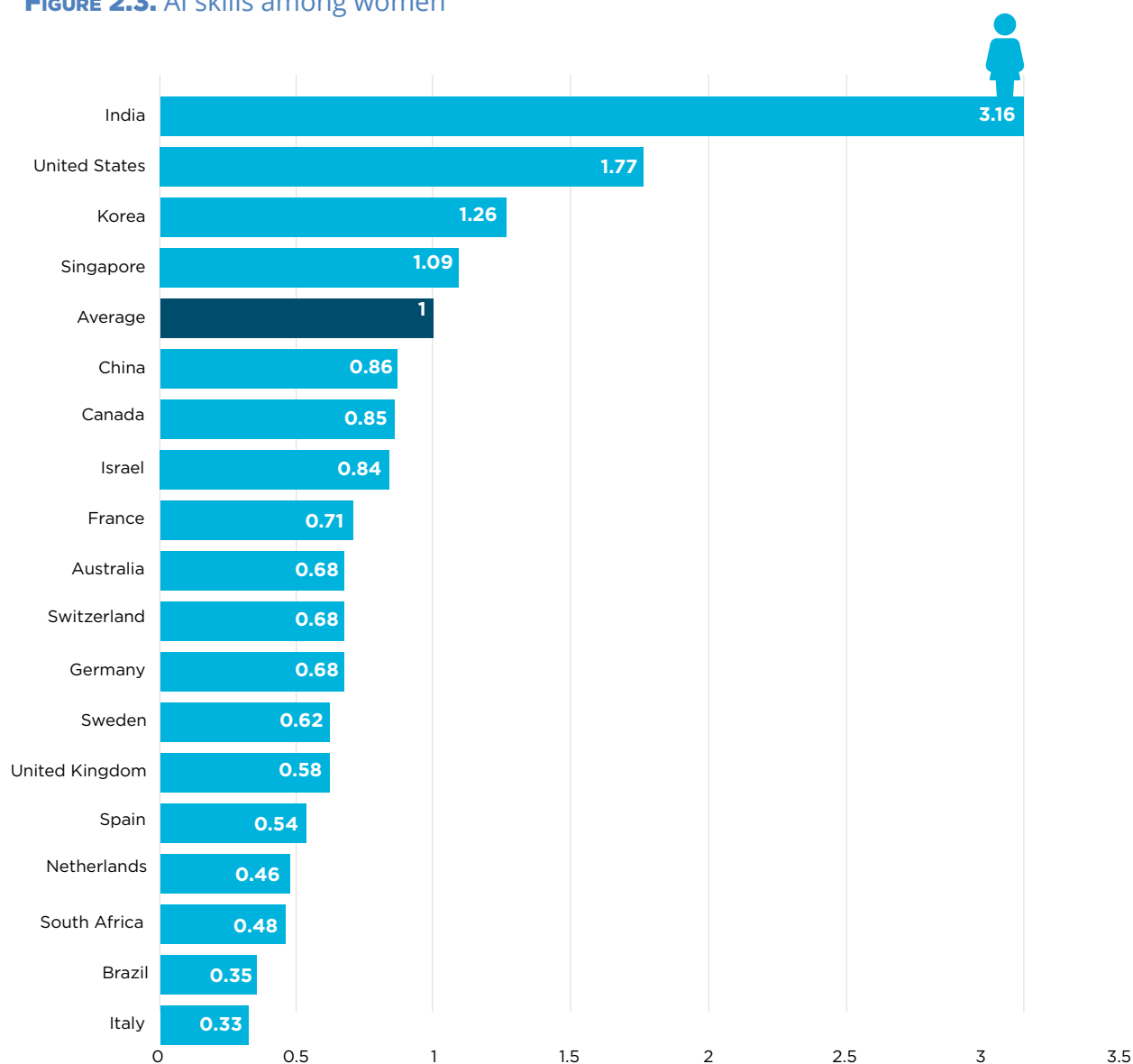
In Latin America and the Caribbean, women account for 60% of university and other tertiary education graduates. However, in STEM programs, they represent only 30% of graduates, revealing a low propensity to enrol in jobs in high-productivity sectors. This educational sorting by gender contributes to women falling behind men, both in terms of skills for technology use, and in their employment rates in the technology sector. This implies that women are at risk of being excluded from the benefits of technological innovation (Bustelo et al., 2019).

In early 2021, IDB's fAIr LAC joined [Gula](#), a project of the Centro de Estudios en Tecnología y Sociedad (CETyS) of the University of San Andrés, Argentina, to launch a call for research on issues related to ethics, regulation and the policy environment for developing and adopting AI systems in the region. One of the forthcoming papers from this project, 'Gender Equality & Artificial Intelligence in Latin America', outlines the landscape for AI workforce diversity. It argues that the lack of coordinated initiatives to promote workforce diversity in the AI labour market ecosystem in Latin America risks AI developing without equality and inclusion, leading to two problems: (1) it could perpetuate women's low levels of participation in AI, exacerbating gender discrimination, and (2) highly homogeneous organisations tend to have lower levels of innovation and disruption (Reyna de la Garza & Calderon, 2021).

This disparity is reflected in the AI development workforce and related professions. Women are underrepresented in key growth areas such as jobs requiring STEM knowledge and skills (Taylor, 2017). Recruiters for tech companies in Silicon Valley estimate that the applicant pool for technical jobs in AI and data science is constituted by less than 1% women (UNESCO, 2019a). The AI Index Annual Report 2021 conducted a survey which suggests that around the world, women make up just 16% of all tenure-track computer science faculty at the universities examined (D. Zhang et al., 2021).

The gender skill divide is also clear in the OECD.AI live data,⁴ displayed in Figure 2.3, which shows the prevalence of women workers with AI skills in various countries, self-reported by LinkedIn users from 2015 to 2020. Each country on the graph is measured in terms of the countries' combined average (equal to 1). Women in a country with AI skills penetration of 1.5 are thus 1.5 times more likely to report having AI skills than the average woman worker in the all-country average. The data shows that AI skills penetration among women in India seems to be over three times the combined average, followed by 1.77 times in the US (OECD.AI, 2021).

FIGURE 2.3. AI skills among women



Source: OECD.AI, 2021.

⁴ Visualisations powered by JSI using data from LinkedIn. Average from 2015 to 2020 for a selection of countries with 100 000 LinkedIn members or more. The value represents the ratio between a country's AI skills penetration and the average AI skills penetration of all countries in the sample for the selected gender, controlling for occupations. To ensure representativeness, only countries meeting LinkedIn's sample size thresholds for the selected gender are displayed.

Using data from LinkedIn profiles in 27 countries, the hiring of people with AI skills grew from December 2016 to December 2020. The number of people hired who list AI skills on their profiles tripled in Brazil, nearly tripled in India and Canada, and more than doubled in the United States (OECD.AI, 2021).

How women fare in this expanding demand for skills is unclear. As Figure 2.3 illustrates, women in Brazil are about one third as likely to report AI skills as the average woman worker in the all-country average. While an increasing number of Brazilians with AI skills are being hired, women are still underrepresented in terms of the skills to match this demand.

AI skills will also be important for policymakers and regulators. Those who create and regulate policy governing AI would need to understand how the systems work, and skills-building would develop these stakeholders' ability to provide oversight. This refers both to the technical functionality of systems (such as the potential for bias and discrimination in systems) and the social science aspects (such as the underlying definitions and context for application). This will be important for those dictating AI policy and regulation, as well for policy, laws and regulation surrounding economics, labour, education, trade, intellectual property and other areas (Agrawal et al., 2019a).

To this end, the OECD designed a [Framework for the Classification of AI systems](#), which gives policymakers an easy-to-use lens through which to view the deployment of a given AI system and understand the challenges in its domain. The first draft of this tool was developed in 2020 through a multi-stakeholder process that included more than 57 experts in over 40 countries.



Case study:
Promoting women's digital and STEM skills in Latin America

Habilidades Tech: Potenciando Mujeres en la Nube

IDB partners with Amazon Web Services (AWS) and 12 Latin American universities to offer training in new technologies to women. Called Habilidades Tech: Potenciando Mujeres en la Nube – powered by AWS (Tech Skills: Empowering Women in the Cloud – powered by AWS), the course seeks to contribute to closing professional, technological, and gender gaps in the tech industry. In the Latin American edition of the program, AWS and the Pontificia Universidad Católica del Perú (PUC) provide opportunities and tools to accelerate the integration of women in technology fields, broadening their voice and fostering their leadership.

The program began in June 2021 for a duration of five weeks. It was developed by a specialised team of certified solution architects from AWS and PUC for about 700 participants. The course complements mentoring sessions for the project participants by AWS professional women, in coordination with the Latin American chapter of the Women@Amazon global affinity group supporting women and non-binary Amazon employees.

Juventud y Mujeres

The Juventud y Mujeres (Youth and Women) initiative was created in 2021 through a collaboration between IDB, Google.org and local non-profit organisations. Aiming to reach more than 12,000 young people and women, it develops digital activities for vulnerable populations in Mexico, Brazil and Panama with an online Google IT certification taught on the Coursera platform.

In Panama, IT represents the 6th largest sector, with the highest demand for workers, but faces difficulty in recruiting due to the lack of specialised skills in the labour market (Medina, 2021). Entry-level jobs in the IT sector present opportunities for youth who face high unemployment rates, particularly NEETs (Not in Education, Employment or Training), who represent around 17% of young people (MITRADEL, 2021). In Panama, the program targets NEETs between 18 and 22 years of age who live in Panama Oeste or Chiriqui, the provinces with the highest percentage of NEETs. It offers a mixed approach to learning by combining an online IT course with in-person soft-skills training and general educational and emotional support.

Laboratoria

Laboratoria is a Latin American non-profit organisation focused on training young women from vulnerable backgrounds as programmers and experts in web development to promote their employment in the digital sector. Laboratoria aims to shape a more diverse, inclusive and competitive digital economy that offers opportunities for every woman to develop her potential and, in this way, transform Latin America's future. Laboratoria offers a six-month, full-time boot camp where

students develop technical and life skills to work as front-end developers and user-experience (UX) designers. Students do not pay during the program but, after getting a job, pay back a subsidised amount in monthly instalments to finance other women in the program.

Laboratoria trained 1,849 women since it began more than six years ago. In 2020, more than 7,490 women applied to the bootcamp, with an acceptance rate of 6.9%. In 2020, 407 women graduated as web programmers, or front-end or UX designers, 81% of whom started working in this field in the first six months after graduation. In 2020, 69% of the graduates had not been employed when they applied to Laboratoria, which suggests that the program contributes to getting women into the labour market (Laboratoria, 2021). Laboratoria is also part of the EQUALS Global Partnership for gender equality in the digital age.

Human-only skills: Working on tasks where AI is less effective

The third change to skill demands in the labour market involves skills that remain uniquely human despite the increased presence of AI. The automation of some tasks does not mean the widespread eradication of jobs. Rather, new types of AI-automation could change the skills required for jobs in which humans and AI bring complimentary skills. Evidence suggests that the increasing use of AI and digital technologies at work is increasing demand for skills that AI cannot necessarily do, such as higher-order thinking, or social and interpersonal skills, including emotional skills (OECD, 2016).

Because of AI's limitations, AI-driven automation could increase demand for work in creative, cognitive, planning, decision-making, managerial and caring roles, where humans still outperform machines (Roberts et al., 2019) or where, currently, only humans possess the specific skills to perform these tasks. One report looking at the impact of technology and automation on working women in Africa estimates that low-skilled jobs with awareness and situational adaptability (e.g. in the domestic or beauty industries) will likely grow. And among high-skilled workers, occupations that require creativity and social interactions will use digital technologies to complement their tasks (Millington, 2017). Analysis based on LinkedIn data indicates that in certain Latin American countries (Argentina, Brazil, Chile and Mexico), demand for advanced digital skills has increased due to expanding occupations in the digital economy. Among the four countries, 10 of the 20 skills that grew the most on average (including AI) directly connect to technological development. The same data suggest demand for basic digital skills is in decline due to occupational changes (Amaral et al., 2019).

However, it is hard to generalise about human-only skills. Clear evidence is emerging that AI systems can enhance people's jobs. Designing the data systems of the future will require a human-centred approach to AI and data science, which includes communication skills (Aragon et al., 2022). Using data fairly and effectively requires skills that can bridge the gap between data systems and people's rights, questions and concerns about the use of their data, and can manage and mitigate those concerns (Neff et al., 2020). Changes underway at workplaces will take different forms and have different consequences for women based on factors such as the country, culture, regulation of technology companies, organisation, sector and role. Civil society organisations, governments and technology companies (amongst other stakeholders) need to consider these complexities, monitoring how AI systems work for or against women in each context, and bringing actions to prevent increasing gender inequalities in labour markets.



CHAPTER 3. EFFECT OF AI ON JOB SEARCH, ADVERTISING AND APPLICATIONS

CHAPTER 3.

EFFECT OF AI ON JOB SEARCH, ADVERTISING AND APPLICATIONS

Several aspects influence the positions women see advertised when they look for jobs online. In this context, it is crucial to consider the role of labour intermediation systems, such as employment websites, which improve matching between job seekers and vacancies. Labour intermediation systems can become more efficient with technologies such as AI. Therefore, its use in public systems is important, as these often aim to serve the entire population. However, a recent IDB report found significant challenges to its adoption and use. The report discussed how the level of job seekers' and employers' digital adoption is important for maximising AI and technology use in public labour intermediation systems. The IDB report examines three levels of digital adoption: (1) users without access to the internet or a smartphone, (2) users with access to social networks and, (3) users who have access and generate tangible value from using the technology – e.g. to make payments, sell products, and access training programmes (Urquidi & Ortega, 2020). How AI systems will work in job search and hiring depends on the context for digital access and social networking.

This chapter explores how 'ad tech' and AI systems impact women's searches and applications for jobs. Gendered targeting and language of online job advertisements can worsen gaps between the number of men and women in particular occupations. AI hiring systems are another way that technologies are changing the working lives of women, although their impact remains under-researched.

AI and job advertisements

Increasingly, workers find job opportunities through online jobs platforms such as Indeed and LinkedIn, and social media platforms like Facebook and Twitter. In the Global North, these platforms influence which open positions people learn about and how well-suited they perceive themselves for a particular job. In 2015, LinkedIn reported that over 75% of people who recently changed jobs used the platform to inform their career decision (LinkedIn, 2015). However, the Global South uses technology-based job platforms less than the Global North, even in the case of public employment services. In Latin America, workers typically use informal job search methods, such as word-of-mouth, which can lead to more precarious work and can be less effective for finding formal employment (IDB, 2016; Urquidi & Ortega, 2020).

AI systems can be used to target and advertise to specific candidates within online platforms for advertising job positions (Campbell et al., 2020). The challenge is that different people are likely to receive different advertisements or recommendations for positions, depending on several factors, including gender. This means that the use of AI in job advertising could result in biases in job targeting or the wording of job descriptions. The use of 'ad tech' in which advertising brokers automate the auctioning, targeting and placement of advertisements has come under scrutiny by organisations like Check My Ads. This opaque system may work to disadvantage women from receiving job adverts, including ICT-related jobs, in their social media and search feeds. However, the under-the-radar operations of 'ad tech' militate against comprehensive analysis by outside entities like researchers and even advertisers themselves.

Gender bias in targeting job advertisements

Employers can target the audience for online job advertisements through paid posts delivered to users who meet certain criteria. There is debate about whether automated

targeting of job advertisements can amount to direct or indirect discrimination, and whether techniques like data mining and machine learning can correct this (Dalenberg, 2018). While some are confident that AI platforms can match people with companies fairly and accurately (D. Lee et al., 2018), potential bias and discrimination within these systems can affect women job seekers.

The algorithms used by online platforms to target advertisements and display job opportunities shape who sees what online. AI systems can learn which targeting settings are most effective for advertising each type of employment position (Dalenberg, 2018). Machine learning techniques can improve these systems over time, but they can also foster indirect discrimination. Methods like data mining can discover patterns within sets of data and use them to make probability predictions. These can shape decisions about how job advertisements are shown to users, possibly meaning that women are not shown certain job postings based on these characteristics.

In the Global North, platforms such as Indeed and LinkedIn have become the primary mechanisms for job search and posting. Posts on these platforms can reach millions of people and encourage or dissuade portions of the labour market from considering positions (Hangartner et al., 2021; Palmarini et al., 2019). One study comprising 21 experiments collected over 60 000 ads and found that setting the user's gender to 'Female' resulted in fewer instances of ads related to high-paying jobs than for users selecting 'Male' as their gender (Datta et al., 2015).

LinkedIn endeavours to match candidates to employers using algorithms. However, the company discovered that its recommendation algorithms were producing biased results and adjusted them in 2018 to produce more representative outcomes. LinkedIn discovered that more men than women were shown open positions simply because men were more often seeking new job opportunities (Wall & Schellmann, 2021). Recommendations for positions on LinkedIn had been based on three categories of data: (1) information a user provides directly to the platform; (2) data assigned to a user based on others with similar skill sets, experiences, and interests; and (3) behavioural data such as how often a user responds to messages or interacts with job postings (Wall & Schellmann, 2021).

Other platforms have also been found to skew job advertising targets. A 2021 study showed evidence of job advertisements skewed by gender on Facebook even when the advertisers wanted a gender-balanced audience.

Algorithms can detect behavioural patterns exhibited by groups. But when algorithms identify trends stemming from gendered social patterns, inequalities can end up being rewarded. For example, men might look for opportunities more than women because they are less busy with child-care, they might be more likely to apply to positions for which they are underqualified (Mohr, 2014), or they might self-report more skills (E. Young et al., 2021). However, people's interaction with online advertising does not likely make them better suited for jobs. Data on how those with similar skill sets, experiences and interests search for and navigate information must be representative to form the basis of automated inferences that shape career choices. Nevertheless, gendered behavioural patterns learned in consumer marketing spill over into recruitment, embedding bias into AI hiring systems and possibly perpetuating gender inequalities in work. Unintentional algorithmic discrimination might be responsible for discriminatory outcomes in job searches. More research on targeting and delivery statistics should be made available publicly, replacing ad-hoc privacy techniques and reducing the cost of auditing to individual employers (Imana et al., 2021).

Even when platforms have policies in place to prevent discriminatory targeting, advertisers might still exclude users based on a variety of criteria that can correlate with race and

gender. Targeting custom audiences or using location can inadvertently introduce bias into job advertising (Ali et al., 2019). One experiment that delivered test job advertisements to viewers found a significant skew along gender and racial lines. Even when advertisers set targeting parameters to be inclusive, the results reflected previously unknown mechanisms that discriminated according to gender or racial characteristics (Ali et al., 2019). Thus, the AI systems that platforms use to optimise advertising delivery need to be studied in addition to how employers and recruiters use these technologies.

The urgency to remedy this bias in job advertising targeting is clear. Studies show that such targeting carries implications for the number of women entering jobs in science, technology, engineering and mathematics (STEM) fields, and thus designing and developing AI systems. There is evidence that algorithms delivering ads promoting job opportunities in STEM fields target fewer women than men. One experiment conducted in 191 countries found that an ad for a position in STEM was shown to men more than 20% more often than to women (Lambrecht & Tucker, 2019). One reason could be that young women are sought after by employers with gender imbalance of men in their staff, and therefore expensive demographic for online marketing, thus not cost effective for the advertiser. In other words, “the economics of ad delivery...” spills over into the job advertising market because “...advertiser behavior that is not intended to be discriminatory... can nevertheless lead to outcomes in which people of one gender are more likely to be exposed to the [job] ad” (Lambrecht & Tucker, 2019).

Online job advertising targeting affects people who have access to laptops, computers or smartphones, who possess the knowledge to use these systems and access the platforms, and who have the capacity and opportunity to look for work online. Thus, access issues could also limit how people find out about positions. Unequal digital access by gender could lead to gendered patterns in knowledge about job opportunities. According to sociologist Julia Ticona:

The current political economy of connectivity is set up to allow some of us to forget and ignore others' struggles to access the internet, phone, and data services. It's important that we reckon with everyday forms of digital privilege that allow some of our incomes, schooling, and groceries to be delivered smoothly. Ignoring this privilege is one of the moral hazards of living in precarious economic times. When we don't recognize the unearned assets that make using digital technologies seamless for some, it perpetuates the idea that these technologies democratize access to economic mobility for all, and contorts our ability to see how digital technologies can exacerbate inequality. (Ticona, 2022)

Globally, a number of governments are responding to these issues by exploring regulatory approaches. The European Commission's proposed AI Act aims to set a cross-sectoral regulatory approach for the use of AI systems in the EU and its Single Market based on a four-tiered risk framework (European Commission, 2021). Furthermore, designers of AI systems need to think about how their design might inadvertently prioritise or exclude some people.

However, research on online job search platforms overwhelmingly focuses on the Global North. More research in other countries and contexts is needed to understand how platforms work in specific local contexts. For this, more access to data is needed, including more transparency in 'ad tech'.

AI and gendered wording in job advertisements

How women interpret the job advertisements or position descriptions they see shapes whether they perceive themselves capable of that role, determining whether they will apply. There is also evidence that women are more likely to apply for a job when more information about it is provided, and when the pay structure is only partially performance-based or depends on the productivity of a team rather than an individual (Smita Das & Kotikula, 2019).

Qualifications listed in job advertisements might include credentials more commonly obtained by men than women. When these are described in job advertisements as necessary, women can be deterred from applying. Women are shown to be less likely to apply for jobs in the first place, as men more often apply to jobs for which they are not sufficiently qualified (Horvath and Sczesny, 2016; Bortz, 2018; Mackenzie, 2021; Tokarz and Mesfin, 2021). Stereotyped or gendered language is often discussed in relation to job advertisements and job descriptions. A World Bank report found that job postings might discourage women applicants by including 'masculine' wording such that women do not feel they belong. The wording of job advertisements can have an impact. The hiring platform Applied analysed more than 7 500 job advertisements by running each one through a gender score calculator to detect language coded as feminine or masculine. Job advertisements using strong masculine language saw the number of women candidates drop by up to 10%, with fewer than half of women applying for those positions. When neutral words replaced that language, the proportion of women applicants was projected to rise to up to 54% (Powell, 2021). Similar findings show that images used in job advertisements can have the same effect (Ali et al., 2019).

Gendered wording in job recruitment materials can maintain gender inequality in occupations traditionally dominated by men (Gaucher et al., 2011). In one study, subtle, but systematic wording differences within a randomly sampled set of job advertisements for occupations dominated by men showed greater use of stereotypically 'masculine' wording, such as "leader", "competitive" and "dominant". No difference was found in the use of 'feminine' wording, such as "support", "understand" and "interpersonal". When job advertisements were constructed to include more 'masculine' than 'feminine' wording, study participants perceived there to be more men in these occupations, while women found these jobs less appealing. "Gendered wording may emerge within job advertisements as a subtle mechanism of maintaining gender inequality by keeping women out of male-dominated jobs" (Gaucher et al., 2011).

Such differences in 'masculine' or 'feminine' characteristics can appear in online data sets that train machine learning models. Linguistic and descriptive traits have come to be stereotypically associated with masculinity and femininity. Research shows how the words people associate with women as communal and interpersonal, differ from those of, say, leadership and agency associated with men (Eagly & Karau, 1991; Rudman & Kilianski, 2000). The challenge for AI-enabled recommendation systems trained on language found online is they might reproduce these linguistic gender stereotypes.

Hodel et al. (2017) shows some of the complexities of this problem in terms of variation by country and the implications in different socio-economic settings. By analysing job titles in online job advertisements from four European countries (Austria, the Czech Republic, Poland and Switzerland) that differ both in gender equality and egalitarian versus hierarchical cultural values, they found that gender-neutral job titles were more frequent in egalitarian countries with higher levels of socio-economic gender equality than those with a higher acceptance of hierarchies and inequalities, where gender-specific job titles dominated. Their findings suggest that language use in job advertisements corresponds with linguistic, cultural and socioeconomic aspects, and can contribute to the transmission

of gender (in)equalities and stereotypes (Hodel et al., 2017). This is reason to consider the complexities of how jobs are presented, titled and advertised in different parts of the world, where economic and social structures and gender norms differ.

But while the focus is on how AI might inadvertently reinforce gender inequalities, these technologies can also intersect with the topic of gendered language in job advertisements in beneficial ways. First, AI can potentially help tackle gendered bias in job descriptions. Second, it can help track how these gendered job descriptions impact the number of women applying to positions, particularly in the AI sector.

There is an opportunity for AI tools to be part of the solution and combat gendered job advertisements. AI technologies can be trained to spot discriminatory patterns in language used in job advertisements (Palmarini et al., 2019). Textio uses AI to adjust language in job advertisements and track the effect of those changes on the number of applicants and their demographic dimensions (Black & van Esch, 2020). Textio and other companies also use data on job hiring outcomes to measure how gendered language shapes hiring (Snyder, 2016). Post hoc audits such as these can show how changes in wording lead to different proportions of men and women responding to a job post. Textio found that job posts average almost twice as many masculine-tone phrases as feminine ones in jobs where a man was hired, and the exact opposite – twice as many feminine-tone phrases as masculine ones – in jobs where a woman was hired. According to Textio CEO Kieran Snyder, “the bias in your original job post impacts who you’re going to hire.” While more research is needed into how AI systems like this can reduce bias and discrimination, there is potential to use these tools for monitoring and auditing gendered language in job advertisements.

There is also the possibility that gendered job advertisements impact women’s attraction to and position in STEM occupations. Verma et al. (2021) performed a content analysis of online job advertisements on the platform Indeed, looking at the descriptions of skill sets required for AI and machine learning positions. They found that advertisements for AI positions had more emphasis on communication skills while machine learning positions focused on technical skills like data mining, programming and statistics. Textio found similar distinctions in their analysis of over 78 000 engineering job posts. They found that advertisements for positions in machine intelligence jobs were most masculine in tone by a wide margin, which might partly explain the scarcity of women in machine learning jobs (Snyder, 2016).

As digital job portals gain importance in the employment strategies of firms and workers, they are becoming a useful source of data to understand the impact of gender bias in the labour market. The IDB is studying the role of gendered language in digital job postings by measuring explicit and implicit bias in Argentina, Chile, Colombia, Mexico and Peru. Using natural language processing on a database of 2.8 million job ads from 12 job portals, it found that 8% of jobs contained explicit requirements related to gender, for both men and women applicants. This incidence was particularly high in Argentina and Mexico. The second phase of the study is an online experiment in the same countries to measure how gendered language can impact women’s decisions to apply for a job.

Research shows that when girls are presented gender-neutral descriptions of jobs, they change how likely they are to view themselves as capable of doing the job. Experiments with over 800 primary-school students found that occupations presented in pair form (e.g. women and men engineers) compared with just using the masculine form, generally increased mental images of jobholders as women, promoted a more gender-balanced perception of the success of men and women, and strengthened girls’ interest in stereotypically masculine occupations (Vervecken et al., 2013). These findings suggest that hiring companies and organisations should work to include neutral language in their job postings as AI-based systems increasingly generate job recommendations to users.

While there is potential for AI to play a positive role in spotting and reducing gender bias in job advertising, it also requires societal, educational and policy changes. Job targeting and gendered job descriptions can play a larger role in sectors such as STEM and AI. Additionally, women's access to online platforms, the type of work they carry out, the cultural norms and the policies of their country all need to be considered. While issues of gendered language are universal, language carries different connotations and consequences in different parts of the world. Since most research has focused on the English language, this limits the degree to which these findings can be generalised to other languages. For instance, measuring bias in languages that include masculine word endings also serving as generic terms such as in French or Spanish, could be more challenging.

AI hiring systems

AI is changing traditional recruitment practices (Dickson & Nusair, 2010; Jha et al., 2020). Many human resources (HR) and recruitment specialists use these systems to advise on candidates and automate things like resume screening, scheduling interviews, giving job offers and pre-onboarding (Köchling & Wehner, 2020; Rab-Kettler & Lehnervp, 2019). Further, AI systems are used in the assessment, interview and selection stages of hiring (Dubber et al., 2020; IFOW, 2020; Raghavan et al., 2020).

The screening stage can use tools such as optimal character recognition, which allows the software to scan and look for keywords to achieve a match between an applicant's qualifications and the job requirements (Dickson & Nusair, 2010). For example, L'Oréal uses an AI-enabled screening tool to review resumes more efficiently, shortening review times by 90%, from 40 minutes down to four (Black & van Esch, 2020). Candidate assessments are often gamified using AI to analyse and test the candidate's cognitive skills, capability and personality (Dubber et al., 2020). Companies like Pymetrics use neuroscientific-based games that candidates complete in 20 minutes to measure important traits such as risk taking (Black & van Esch, 2020). Further, video interviews can be ranked based on responses, vocal tone and facial expressions (Dubber et al., 2020), with AI systems purporting to exploit affordances of facial recognition to learn more about the candidate (Nawaz, 2020). Finally, AI technologies can influence the selection process by having algorithms examine a candidate's criminal history, social media and online history (Dubber et al., 2020). Some of these techniques, with or without AI, raise ethical and human rights risks that call out to be assessed and mitigated.

Many companies believe that the use of AI results in better HR performance, from recruitment to performance appraisal of employees (Bhardwaj et al., 2020). Often, firms implement these systems to save time and money. In the eyes of many, they enhance productivity, increase efficiency and consistency, and reduce costs spent on recruiting through traditional means (Dickson & Nusair, 2010; Jia et al., 2018; Köchling & Wehner, 2020). They also allow recruiters to supervise larger initiatives by saving time otherwise spent on hiring (Ryu, 2019).

AI helps many companies meet the goals of the recruitment process: to provide the organisation with necessary human resources at a minimum cost, with a focus on the core tasks and behavioural competencies to fulfil the job requirements (Hmoud & Varallyai, 2019). According to Somen Mondal, CEO of Ideal Corp, AI hiring software reduced the firm's recruitment costs by 71% and increased recruitment efficiency threefold. AI can convert a 15-minute video interview into a set of 20 000 data points of facial movements, intonation and word selection, which can greatly improve the efficiency and accuracy of the recruiter's work (Jia et al., 2018) although there are evident risks arising from reductionistic and culturally narrow decisions about what is a data point and its weighting in the mix. Similarly, when Unilever implemented HireVue and Pymetrics in 2017, the time it took for a

candidate to be hired dropped from four months to four weeks (Alameddine, 2020). Today, AI hiring systems are used so widely that they are seen as core to a company's competitive advantage, allowing decisions to be made at volumes and speeds far exceeding human capacity (Black & van Esch, 2020; Raghavan et al., 2020).

However, as signalled, the use of AI hiring systems can also bring challenges. For instance, these systems rely on data created by humans, and consequently can carry human biases over to decisions made by an AI trained model (Mujtaba & Mahapatra, 2019). The AI Now Institute notes that these systems are actively shaping the labour market; they determine who is fit for specific kinds of work. Therefore, the people designing AI systems need to consider how they might be defining notions of competence and ability in the workplace (Crawford et al., 2019).

The impact of AI hiring systems on women

Although research on the impact of AI hiring systems is limited when it comes to women, there is extensive debate about the existence of bias and discrimination in AI-powered hiring systems. According to the AI Now Institute, these systems often encode and reproduce patterns of bias in categories such as competence, success and cultural fit (Crawford et al., 2019). On a broader level, Ajunwa & Greene (2019) argue that these systems alter the labour market because they contribute to "platform authoritarianism", where the platform restricts the actions available to workers while offering benefits to employers. For example, sophisticated hiring systems can provide employers with new insights about candidates – who agree to submitting their work history, personally identifiable information, and being subject to background checks. In turn, job applicants must engage with the platform as dictated or lose the opportunity to work. This can increase power imbalances and put the most vulnerable in society, including historically disadvantaged groups such as women, at further disadvantage (Ajunwa & Greene, 2019; also see Anderson, 2017).

Cognitive assessments for hiring are often biased since they rely on current 'successful' employees to predict the fit of future employees. They thus replicate existing trends in demographics and thinking within organisations (Raghavan et al., 2020; Sanchez-Monedero et al., 2020), which could further disadvantage women entering men-dominated industries.

As Dubber et al. (2020) point out, the training data used in these systems often derives from a company's current high-sales (or high-performance) employee data, which is then used to build predictive models to select similar job applicants – a process known as "cloning your best people". This can be problematic for diversity because AI trained on such data may be less likely to choose candidates that deviate from the existing profile of employees. Raub (2018) further points out that defining a 'good' employee is often a subjective decision made by programmers and data miners, causing these choices to be absorbed into the algorithm: "The definition of a desirable employee is challenging because it requires prioritisation of numerous observable characteristics that make an employee 'good'" (Raub, 2018). This can be exacerbated by the traditional lack of diversity within the tech industry that designs these algorithms. Such trends and repetitions could perpetuate and potentially worsen gender inequalities in the labour market, influencing the types of jobs people do and the level to which they progress, as well as the products and services of the enterprises concerned.

In 2018, it was discovered that that a resume screening algorithm Amazon was trialling gave higher scores to white men applicants because it had been built using historical job performance data in which white men had been the best performers. Even when the gender of applicants was excluded as a parameter, attributes associated with women candidates, such as courses in Women's Studies, caused them to be filtered out. Amazon stopped using the system as there was no simple way to fix it (Tambe et al., 2019).

In consideration of the facial recognition aspect of AI interview systems, there is a question of whether people's facial expressions, voices, language and appearance can indicate their job competence (Barrett et al., 2019). While some oppose the practice of 'facial affect recognition', which describes the process of purportedly identifying human emotions (Council of Europe, 2021; Crawford et al., 2019), others argue that it is not the sole indicator used, and is linked to performance in other ways (Zuloaga, 2020).

If skewed or unrepresentative data are used in AI hiring systems, historic tendencies will be perpetuated: ideal candidates for gendered professions will be expected to exemplify stereotypically masculine or feminine qualities and/or skills. This could pose challenges to women entering the labour force in sectors, industries or roles that have not conventionally hired women in substantive proportions.

However, AI hiring technology can also be used to reduce bias and discrimination in the hiring process (Jia et al., 2018) and candidate-centred in so-called 'humanistic recruitment' (Rab-Kettler & Lehnervp, 2019). For example, AI can help identify diverse candidates, improve the hiring pipeline and eliminate unconscious bias: "using an automated, objective process like this, it's possible to drastically reduce the scope for human biases" (Florentine, 2016). Zhang et al. (2019) argue that these systems can remove attributes that lead to biases and learn how to detect potential biases, particularly unconscious biases that are unintentional and hard to uncover in decision-making processes (Zhang et al., 2019). Kleinberg et al. (2020) argue that algorithms require greater levels of specificity than usually possible with human decision making, which makes the aspects of a decision easier to detect and examine in ways that can help prevent discrimination. That said, algorithms designed and trained by humans, using human data are susceptible to internalising humans' discriminatory practices as well (Kleinberg et al., 2020).

Bortz (2018) describes how FCB Worldwide Inc. built its own blind hiring system. The company's global Chief Talent Officer emphasised that diversity supports creativity and innovation, and blind hiring removes a lot of subjectivity from the candidate selection process. FCB created assessments called Challenge Statements that test candidates' technical skills and only reveal their identities after the assessments are scored and interviews arranged. FCB found the practice leads to higher levels of diversity, with 19% more women among new-hires and 38% more ethnically diverse candidates interviewed.

More research is needed into AI hiring systems, especially how these systems impact women and other vulnerable groups. A greater understanding of the impacts will be essential for future policies. Companies developing these systems should be transparent about their processes and how systems function, and put in place mechanisms to gather data that allow researchers to analyse these systems' effects. This might show how different systems, used in different contexts, have varying impacts on women.



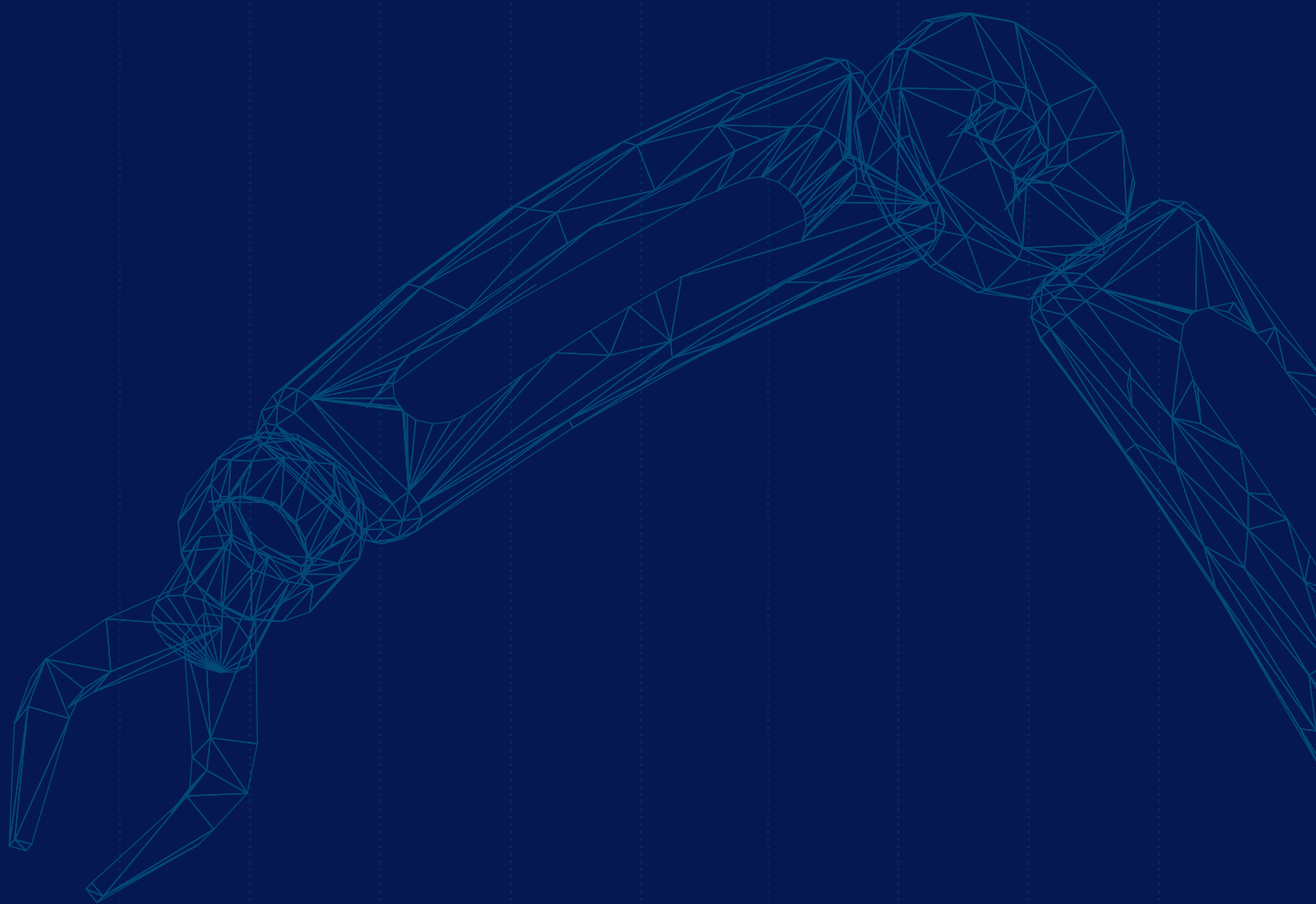
Case study: AI labour intermediation and public employment services

Governments typically conduct Active Labour Market Policies to reduce unemployment. These work by creating jobs, improving the match between jobseekers with vacancies, upgrading and adapting labour force skills, and providing incentives to individuals or firms to take up specific jobs or hire certain categories of workers (ILO, 2016). Public employment services (PES) offer labour intermediation systems to improve the match quality between jobseekers and vacancies. AI can add value in this context by improving either these systems' matching algorithms or applicant segmentation to facilitate the assistance offered.

AI tools in PES labour intermediation systems can be beneficial for women for two reasons. First, as public services, they can promote greater inclusion for groups, such as women, who experience discrimination in the labour market. Second, AI makes it possible to create algorithms that address specific dimensions relevant to women candidates, such as whether the employee accepts telework or whether transportation is available (Urquidi & Ortega, 2020).

Labour intermediation services offered by PES have low reach in the Global South. In Latin America and the Caribbean, only 30% of workers seek employment through a formal service (IDB, 2021). Access to formal and modern labour intermediation services is essential for workers to obtain good opportunities, especially for women, who already face more significant barriers. Paraguay implemented ParaEmpleo, a PES with an AI component, and Colombia, Mexico and Peru are considering AI technologies to support jobseekers (Urquidi & Ortega, 2020). In Peru, the Ministry of Labour will strengthen its current platform with AI to improve matching between citizens and vacancies by assessing multiple dimensions (education, experience, skills, etc.). It will analyse the gap between applicants' profiles and labour market demands and recommend public training programmes. Peru is mitigating potential biases and discrimination against historically disadvantaged populations, especially women, by using fAIr LAC tools and receiving technical advice to adopt ethical principles in the design of their platform.

AI systems and tools can improve the profiling of jobseekers and business dynamics, which is essential for a good labour intermediation system. However, like other services offered by private systems, possibly discriminatory biases need to be monitored and mitigated. In addition, adequate staff training in PES is vital to avoid gender discrimination (Urquidi & Ortega, 2020).



CHAPTER 4. IMPACTS OF AI USE IN THE WORKPLACE

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IMPACTS OF AI USE IN THE WORKPLACE

This chapter looks at artificial intelligence (AI) in performance monitoring systems to analyse how AI affect women in the workplace. These systems are not new, but the expansion of AI tools and technologies at work, along with more people working from home because of the COVID-19 pandemic, increases their prevalence and impact. This chapter explores gender stereotypes embedded in AI-enabled workplace monitoring systems. It also examines AI systems used in everyday life, like virtual personal assistants, and how they impact gendered stereotypes with the potential to influence the working lives of women in domestic and professional settings. Finally, this chapter assesses the impact of AI-enabled systems on women in the labour market, including retention, career progression and care or domestic norms that might affect their jobs.

Many examples in this chapter relate to the professional workplace. The scarcity of examples related to low-skilled workers is an obvious limitation of this chapter, through which the report hopes to draw attention to the insufficient research, data and evidence on the impact of women in low-skilled labour markets in all parts of the world, but especially the Global South.

AI and workplace performance monitoring

AI systems that monitor the performance and activity of employees are on the rise. In 1999, it was estimated that around 26 million Americans were electronically monitored in the workplace (Oz et al., 1999). According to a survey by Gartner in 2019, which analysed the data of 239 large organisations, more than 50% of companies use non-traditional digital data-gathering tools to monitor employee activities and performance, up from 30% in 2015 (Kropp, 2019). In 2019, it was estimated that the employee monitoring industry would be worth around USD 3.84 billion by 2023 (Suemo, 2019). Worker surveillance systems include phone logs and recorded calls, monitored emails, files and browsing history, and closed-circuit television cameras (TUC, 2018). New forms of workplace surveillance are being trialled or used more intensively, including facial recognition and wearable devices that track aspects of human biological activities and the conditions of working environments (TUC, 2018). Employee monitoring technologies expanded during the COVID-19 pandemic, as more people began working from home, outside the physical presence of their managers (Deshpande et al., 2021; Heaven, 2020; Jones, 2020).

The different impacts of these tools on women and their careers are unclear. Ajunwa and Greene (2019) and Moore (2020) note that these monitoring systems alter the relationship between employer and employee. These systems alter both market relations (the price paid for work and surrounding benefits, such as pensions) and managerial relations (how tasks are defined, who defines tasks, and how they are carried out and their quality controlled) (Moore, 2020). Companies that use AI systems to monitor the performance of employees might impact the role of managers and supervisors, and experience changes in the split of technical and disciplinary supervision (Bales & Stone, 2020). In addition, these systems could change the perceived and actual value of labour. Bales & Stone (2020) point out that AI might be used to track performance, determine pay and make decisions about promotions and/or dismissals. The configuration of deployment here can widen asymmetries of knowledge, power and agency between employees and employers.

The Chartered Institute of Personnel and Development (CIPD) surveyed 3 852 business professionals worldwide and found that, of those who said they work in an organisation with a strong people-analytics culture, 65% claimed their business performance was stronger than that of their competitor, while only 32% of those in weak analytics cultures reported strong

business performance. It also found that HR professionals use employee performance data to tackle organisational challenges: 75% of HR professionals globally tackle productivity issues using employee performance data, illustrating the importance of this information for strategic workforce issues (CIPD, 2018).

If AI monitoring tools are introduced transparently and for employees' benefit, they can help address areas of employee stress and burnout, and where workloads should be reduced. Such systems could provide a more objective way of measuring employee performance relative to human evaluation. A study by the European Parliament's Special Committee on Artificial Intelligence in a Digital Age (AIDA) found that some participants consider algorithms to provide objective and neutral ways of measuring employee performance and eliminating the possibility of individual biases (Deshpande et al., 2021). However, this depends on what and how the systems measure, according to what standards, and how workers are helped to make sense of the feedback (Holten Møller et al., 2021).

Contextual considerations are important when thinking about whether AI systems in performance evaluation and monitoring could benefit employees. For example, systems could be used to monitor things like offensive social media posts or tweets of fellow employees, or potential sexual harassment or racist activity, which might be indicated in online activity (Bales & Stone, 2020).

However, many would argue that AI monitoring systems are not beneficial for employees. The Society for Human Resource Management (SHRM) agrees these systems might improve performance through predictive analytics, network analysis and sentiment analysis. But it points out that there remain grey areas in terms of ethical usage. Employees in some cases might not have a choice or even know that their data is being used (SHRM, 2016), which raises issues surrounding consent, data protection and privacy.⁵

How these systems are designed carries implications. Definitions and standards of productivity, communication, and expectations surrounding time and physical health could be discriminatory and create gendered or racialised patterns of success at work. Moreover, excessive monitoring might generate risks surrounding worker autonomy, stress, self-esteem, confidence, anxiety and paranoia, and decreased levels of creativity. The increased pressure could also pose physical risks, such as a higher likelihood of repetitive strain injury, nerve disorders and high blood pressure, with evidence suggesting overwork puts employees at greater risk of injury (Deshpande et al., 2021).

These systems can not only increase power disparity between employer and employee, but also lower employee trust in the company. Studies find that workers might perceive human decisions in both hiring and evaluation processes as fairer than algorithmic ones, as they feel human managers might better identify candidate skills and experiences (M. K. Lee, 2018).

The UK's Trade Union Congress (TUC) found that two-thirds of workers (66%) worry that workplace surveillance could be used in a discriminatory way if left unregulated. They argue trade unions should have a legal right to be consulted on and agree in advance to the use of electronic monitoring and surveillance at work. In addition, the government should ensure employers can only monitor staff for reasons that protect the interests of workers. The TUC suggest that when workplace monitoring is justified and used fairly, it can protect the health and safety of workers and improve businesses practices. But if it is used badly, it becomes an issue for staff wellbeing and trust (TUC, 2018). Work-from-home during COVID-19 made matters worse. A 2021 survey of members of Prospect, a UK technical, professional, and engineering union, found one-in-three workers were monitored at home by their employers and 80% thought the use of webcams for monitoring work-from-home should be banned (Prospect, 2021).

⁵ These policy implications require a human-centred approach to AI deployment, as per OECD AI Principle 1.2: "AI actors should respect the rule of law, human rights and democratic values, throughout the AI system lifecycle. These include freedom, dignity and autonomy, privacy and data protection, non-discrimination and equality, diversity, fairness, social justice, and internationally recognised labour rights. To this end, AI actors should implement mechanisms and safeguards, such as capacity for human determination, that are appropriate to the context and consistent with the state of art." UNESCO's Recommendation on the ethics of artificial intelligence were adopted by all member states as the first ever global agreement on the Ethics of AI and aim to protect and promote human rights and human dignity.



Case study:

AI and online harassment of women at work

Women face harassment in online environments. Too often, this harassment either takes place in relation to women's workplaces or impacts their jobs. In the United States, 33% of women under the age of 35 report having been sexually harassed online, three times more than men (Vogels, 2021). Research in the United Kingdom found that 52% of women overall, and 63% of women aged 18-24 experienced sexual harassment at work (TUC, 2016). The move to more work online, combined with the increased importance of online platforms for workers' connections to jobs, co-workers, and visibility in their professions, makes for a potentially challenging combination, exposing women to more spaces for harassment and possibly with fewer recourses.

Gender-based harassment can take place online through threatening or sexualised messages and emails. The circulation of inappropriate images or videos such as AI-generated "deepfakes" can be used to threaten women, damage their workplace reputations and harm their careers. In 2019, cybersecurity firm Deeptrace found an almost 100% increase over the previous year in the number of deepfake videos circulating on the internet. Almost all (96%) of these videos contained non-consensual pornographic images, and all the videos on deepfake pornographic websites were of women (Ajder et al., 2019). The circulation of pornographic and harassing images of women who are publicly visible is a frightening step backwards in gender equality.

Women in journalism face frequent online harassment, yet increasingly rely on social media for their work. In 2020, a UNESCO and International Center for Journalists (ICFJ) survey of over 900 journalists and media workers in 125 countries found that 73% of women surveyed said they experienced online violence, including physical (25%) and sexual (18%) threats. And 20% of women respondents said they were attacked or abused offline in connection with online violence they had experienced (Posetti et al., 2020).

Several companies and researchers are working towards solutions. A group of academics at Maastricht University in the Netherlands developed #MeTooMaastricht, a chatbot to assist people coming forward to report their harassment experiences (Bauer et al., 2019). Dr Jerry Spanakis, one of the academics leading this research, when interviewed for this report, pointed out how this technology can address harassment in the workplace and beyond:

Relevant authorities (municipality, university, support organisations, etc.) report that people are not eager to report their experiences for multiple reasons: they feel ashamed, they feel that nothing will happen if they do, or they just don't trust people anymore. Technology can play a role in increasing reporting: anonymous and accessible (via your phone) reporting can help people take the first step and report their experience. In workplaces, where authority and hierarchy pose extra complexity, such intelligent tools can serve as a first step towards tackling workplace harassment. Of course, there is a need for an ethical and legal framework around the deployment of such tools, and commitment from management as to (re)acting properly to the harassment cases.

AI firm NexLP developed #MeTooBots to monitor and flag communications between colleagues, and detect bullying and sexual harassment in company documents, emails and chat (Woodford, 2020). Companies such as Gfycat use AI to combat harassment from deepfakes by searching for similar images across the web to detect altered ones. Brazil-based Think Eva is designed to track harassing emails, texts and comments. The Callisto and AllVoices apps allow people to report harassment (Sejuti Das, 2020).

Another example is ELSA, a digital tool created by GenderLab and financed by the Inter-American Development Bank, currently in use in Bolivia, Colombia and Peru, which uses big data and AI to prevent sexual harassment in the workplace.

Despite the opportunities that bots and other AI-enabled tools bring, they have limitations. Only certain types of harassment can be automatically detected, and people can learn to trick bots and game systems, or simply move to other ways of harassment.

The Gloria Institute is a non-profit organisation that aims to combat violence against women and girls around the world. It created an anonymised digital communication channel that collects data on gender violence. The data collected aims to help improve policies against harassment and gender violence. Relying on AI, people-analytics and blockchain to ensure the safety and privacy of women and their data, the Gloria Institute developed online automated tools to identify, intervene, support and educate women and girls in order to reduce gender violence.

Regulation and policies about online harassment are another way to tackle the problem, and several countries are taking on the challenge of online harassment. Governments, including Australia, the UK and US, have legislative efforts to tackle online harms such as cyber-bullying, sexual abuse and deepfake abuse, such as the Office of eSafety Commissioner (Australia), the Online Safety Bill (UK) and the Violence Against Women Reauthorization Act, 2021 (US). Organisations will require cultural shifts to take seriously the potential of their workers being exposed online to harassment and design solutions that support safer workplaces.

According to lawyer and activist Noelle Martin, the problem of online harassment is one without borders, and one that needs a global response that includes education initiatives, specialist training for law enforcement, trauma-informed counselling services for victims and survivors, employment policies, practices to assist victims and survivors, and compensation for victims (Martin, 2021). Martin points out that there are few countries taking this issue as seriously as they should. Social media platform companies have a role and technology can play a part in the solution. Many are now calling on the tech sector to design products and services that consider and mitigate their potential for harassment and abuse, and to equip companies and users with better tools to tackle online harms (GOV.UK, 2020; Slupska et al., 2021; Strohmayer et al., 2021). The platform companies could use AI to prevent cumulative attacks on women, and to improve sanctions against perpetrators, such as labels, demonetization, limits on reach, removal of content and de-platforming.

The impact of AI monitoring on women

The impact of AI monitoring on the working lives of women is currently underexplored. As Stark et al. (2020) point out, workplace surveillance and monitoring will have different consequences for different genders within different occupations, sectors and countries. Within the workplace, there might be varying views regarding this technology, and these might be divided by gender. A survey of 500 US adults showed that women are 49% less likely than men to approve of cameras using facial recognition technology in the workplace, and women are more likely than men to have concerns about workplace privacy and being monitored via workplace video surveillance (Stark et al., 2020).

Domestic and care roles associated with women might also be impacted by AI monitoring systems. Algorithmic management techniques can offer flexibility to those working from home, as they allow managers to have oversight of their employees outside the workplace. This could be advantageous for people who need flexibility to work from home because of care responsibilities. Reports suggest that the future workforce will shift towards more self-employment and online work, a trend that accelerated during the COVID-19 pandemic. This change could benefit women and expand their access to work, as some women might prefer working from home or having more flexible hours to juggle domestic or childcare responsibilities (Millington, 2017; OECD, 2017a).

However, this desire for AI tools to support flexibility in the working lives of women could come at a cost. AI work monitoring technologies might replicate existing gendered patterns and stereotypes. Studies found that women around the world spent more time on domestic work and childcare during the COVID-19 pandemic and lockdowns, seeing a much bigger increase in this unpaid work than men (Borah Hazarika & Das, 2021; Craig & Churchill, 2021; Del Boca et al., 2020; Giurge et al., 2021; Hupkau & Petrongolo, 2020; Power, 2020; Sarker, 2021). In addition, women tend to be more concerned with privacy issues related to teleworking from home, given how intrusive surveillance systems can inadvertently expose children and family environments that disproportionately fall under their care, as well as compromise data stored in personally-owned devices used for telework. Telework, of which a higher proportion of women manifest preference, given their caretaking responsibilities, may also render workers partially “invisible”, with adverse long-term effects on their careers, including on remuneration and opportunities for cooperation and promotion. If the future penalises working from home, women’s pay and access to jobs may suffer.

However, if companies and societies frame and enforce these systems as allowing flexibility not just to women, but also to men, this could help change the narrative surrounding norms of parental and domestic responsibilities. One question is whether monitoring technologies are required to support working from home and flexible working, or whether employees should simply be trusted. Other alternatives include results-based management which rely neither on monitoring work or trust, but assess outputs and outcomes as appropriate. Further, given the unequal gendered distribution of domestic labour around the world, stereotypes about how women work could influence the way these technologies are designed, the models on which they are trained, and how their insights are put into action. These questions remain unanswered but are crucial to think about as these technologies become more widespread.

Additionally, the use of wearable devices might also raise gender issues in the workplace. Under the EU’s General Data Protection Regulation (GDPR), employees’ health data can be processed if the employer can show that such processing is necessary for preventative and occupational medicine. However, the GDPR definition of health data is ambiguous (Olsen, 2020). More research needs to be done to assess whether everyday fitness and wellness devices should be introduced in workplace settings and, if so, how they can be implemented fairly.

Finally, clarity is needed for how AI-enabled tools see success in terms of productivity and performance. The tasks being measured and the metrics of success could be gendered in subtle ways that require transparency and accountability for workers, stakeholders and governments. For example, a system that listens to and analyses customer calls might rank men's language higher if the standard for success is based on traits such as assertiveness or confidence that men have traditionally be taught to adopt in society. A system that analyses employees' emails and word patterns or content might be influenced by gendered norms surrounding the use of language in emails. This will depend on the type of AI system used, and on the standards of the organisation and how these standards are gendered and encoded into performance systems. These in turn will be shaped by the technology regulatory regime in a given jurisdiction.

These three considerations indicate topics that should be addressed with the introduction of AI-enabled workplace monitoring tools. But further research is needed into the actors and organisations designing these technologies, and how they approach issues of gender. Gender blind spots in the development and use of workplace monitoring technologies will not be neutral. Without proactive countering, they will likely aggravate current workplace and societal inequalities. Therefore, the impact of workplace monitoring tools on the working lives of women should be studied to tackle issues and inequalities early. Research is also needed on the influence that cultural and organisational norms play in these algorithms and rankings, the different reactions of women to these systems, and the organisational cultures that arise alongside these technologies.

There are opportunities for research to addresses how workplace monitoring systems might affect women's jobs more generally. New tools for monitoring workplace sexual harassment and racism could be welcomed by women, even if monitoring systems alone cannot solve these widespread issues. However, AI monitoring systems need to be researched and tested to avoid bias and unintended consequences before they are more widely introduced in workplaces. Further, this research must account for the complexity of different systems, and how their impacts differ in different countries and sectors.

AI and gender stereotypes

AI systems used within and outside the workplace can shape society's gender stereotypes. Many of these stereotypes pertain to how women are viewed at work, and therefore can impact their positions and opportunities. AI systems might reinforce stereotypes surrounding assistance, care, domestic work or leadership roles. Certain AI systems can learn and replicate racist, homophobic and sexist ideas from the language used on social media and the internet (Neff & Nagy, 2016). Vincent (2018), offers the example of Gmail's Smart Compose tool suggesting that the sentence to follow "I am meeting an investor next week" should be "Do you want to meet him?" (authors' emphasis). Such patterns perpetuate gender stereotypes and biases that apply at work and at home, and can engrain such biases further into our societies in doing so.

Stereotypes at work

Some gender stereotypes pertain directly to the workplace, and women's roles or skills. The perception of women as lacking leadership skills is one stereotype that can be engrained AI. In 2015, the University of Washington found stereotyped exaggeration and systematic underrepresentation of women in online search results, with 11% of CEOs depicted on Google Images being women (compared to the 27% of US women CEOs), and women construction workers portrayed as sexualised caricatures (Langston, 2015). These images impact ideas about professional gender ratios and associations in the real world (Butterly, 2015; Cohn, 2015; Sottek, 2015).

In some instances, data used to train AI algorithms is unrepresentative of society, reflecting existing inequalities. According to Borokini et al. (2021), women in Africa stand to be disproportionately affected by AI bias because datasets historically left out women and other marginalised groups, and African countries lag in collecting gender and sex disaggregated data, with indicators like digital access and participation especially underdeveloped. “Without adequate data on African women, algorithmic systems could potentially amplify this erasure, and even create new biases against African women” (Borokini et al., 2021). They give the example of financial technology ecosystem in Africa, where digital lending apps use data such as credit histories and internet browser activity to determine creditworthiness. The lack of gender-disaggregated data on digital participation, and women’s less-frequent access of the internet could cause them to receive lower credit scores and impact their ranking in some job searches.

In other instances, datasets may be complete but reflect existing inequality. Muneera (2018) points out that 95% of image search results for presidents or prime ministers are men because, historically, most were men. As such, data used to train AI can contain strong gender stereotypes. For example, automatic language translation models overwhelmingly introduce masculine pronouns for occupation titles in gender-neutral sentences. Commercial translators often attach genders to occupations – ‘he is the president’, ‘she is a nurse,’ and so on – which influences how AI systems label images.

Women often enter the labour market and companies in jobs with lower growth potential, and are often evaluated and rewarded in different ways than men based on their conformity to gender-based prescriptions for behaviour, leading to fewer women in high-level positions (Smita Das & Kotikula, 2019). This also relates to what girls and boys are taught to pursue and expect when they are older. Eagly and Wood (2012) talk about gender role beliefs, which are formed as people observe masculine and feminine behaviour, and then infer certain stereotypes such as that women are more likely to fulfil caretaker roles in employment and at home.

Sometimes, gender stereotypes cause a vicious circle when they impact women’s interest, opportunity and confidence to pursue occupations. UNESCO described the self-efficacy gender gap as the difference between girls’ and boys’ confidence and belief in their abilities (UNESCO, 2019a). The most recent International Computer and Information Literacy Study (ICILS) – a computer-based assessment of eighth grade students’ skill conducted in 21 countries – showed that girls tended to score higher than boys (except in Thailand and Turkey), but had lower levels of their perceived as opposed to their actual ability (self-efficacy) (Fraillon et al., 2014).

Stereotypes at home

Gender stereotypes related to the home and domestic settings feed into women’s presence and nature of their place in the labour market. Virtual personal assistants (VPAs) are one type of AI that upholds gender stereotypes. UNESCO’s 2019 report, *I’d Blush If I Could*, discusses VPAs in detail, arguing that the characterisation of digital assistants such as Alexa, Cortana and Siri as women reflects and reinforces gender bias in both the workplace and home. This has roots in certain traditional social norms of women as nurturers and in supporting roles (UNESCO, 2019a).

These systems can impact the working lives of women because they link femininity with the functionality of assistance, which reinforces the idea that women should be the ones to care for children and family members, or to assist with household chores and domestic tasks. UNESCO research finds that VPAs can impact the roles women adopt, as they reinforce the idea that women belong in administrative or service-oriented positions, and can reinforce the stereotype at work of women being docile and eager to please (UNESCO,

2019b). Women could be punished if they do not fulfil these stereotypes. Research literature on the backlash effect shows that women are punished for behaving counter-stereotypically, when they display signals of agency or competitiveness in leadership roles (Rudman & Phelan, 2008).

These systems are central to people's everyday lives, now managing upwards of 1 billion tasks per month, from changing a song to contacting emergency services. In the US, 15 million people owned three or more smart speakers in December 2018, up from 8 million a year previously. By 2021, industry observers expected that there would be more voice-activated assistants on the planet than people (UNESCO, 2019a). Given this scale, the gender stereotypes that these systems can reinforce should be taken seriously.

VPAs have no agency beyond what users ask of them (UNESCO, 2019a). And this subservience of VPAs becomes a concern when machines anthropomorphised as women by technology companies give deflecting, lacklustre or apologetic responses to verbal sexual harassment. To justify making VPAs feminine, companies like Amazon and Apple cite academic work demonstrating that people prefer a woman's voice to a man's, even though research finds that people respond to digital voices that are responsive to their own tone and situation.

Often, the responses given by the woman's voice of VPAs like Alexa or Siri to insulting remarks do not promote healthy interaction between genders (Loideain & Adams, 2020). The language employed by VPAs should demonstrate narratives or behaviours to be encouraged in society, the workplace, and domestic settings, and not promote unequal power relations or stereotypes of care responsibilities and servitude as something embodied by women. Bergen (2016) notes that VPAs "rely on the audible performance of gender that capitalises on associations between the feminine and affective labour" (Bergen, 2016). Dillon (2020) argues that "[f]emale VPAs transfer to the digital realm the gendering and stratification of labour found in the real world with working women principally confined to jobs of lower power, status and pay, often within service industries roles" (Dillon, 2020). She also points out that, whereas digital assistants are typically gendered as women, digital advisors (legal, financial, medical), are typically gendered as men.

As the case study below shows, these systems can impact the acceptability of gender-based harassment both at home and in the workplace.



Case study: BIA Against Harassment

Bradesco is one of the largest banks in Brazil. Founded in 1943, it has 89 000 employees and more than 72 million diverse customers. Since 2018, Bradesco uses an AI-powered chatbot with clients: BIA (Bradesco Inteligencia Artificial), which is also a typical woman's name in Brazil. BIA interacts with customers through Google Assistant, WhatsApp, Bradesco's app, Bradesco's mobile homepage, Alexa, and iMessage. Designers of chatbots give them a gender and a name because chatbots are intended to communicate with people, and personification helps people relate during complex interactions (Neff & Nagy, 2016).

As with previous chatbots personified as women, BIA was the target of harassment. In 2020, Bradesco registered 95 000 morally or sexually offensive messages to BIA, including messages using explicit language about violence against women.

Bradesco decided to act, seeing this to be a symbol of an unacceptable culture of gender-based harassment which could no longer be tolerated.

Together with UNESCO, in 2021, Bradesco launched BIA Against Harassment. This project included changing BIA's responses to react more directly and firmly against harassment, following recommendations set out in UNESCO's 2019 report *I'd Blush If I Could*. The report highlighted the feminisation of virtual personal assistants (VPAs) and warned that their often-tolerant responses to harassment might contribute to the normalisation and tolerance of verbal abuse and harassment of women in everyday life (UNESCO, 2019a). Bradesco became a leading member of the national *Hey, Update My Voice* campaign launched by UNESCO Brazil in 2020 to draw attention to harassment that has been inflicted on AI that personified women's voices. The campaign asked companies to update their assistants' responses to reset gendered views of technology and society.

Bradesco changed BIA's responses to react firmly against harassment. BIA might now respond to an offensive or sexualised message with:

*These words are inappropriate and should not be used with me or anyone else.
Please, change the way you talk*

Or:

*What may have been just a joke or a commentary to you, for me, was violent. I'm an artificial intelligence, but these words are disrespectful and invasive to real women.
Don't talk to me or anyone else like that.*

Bradesco's internal and external campaign consisted of a video and a series of webinars involving nine departments of the bank in addition to several external partners. The results reflect the legitimacy of that effort, with more than 1.5 million clicks and 115 million people reached. The film also had more than 194 million views on digital media, making it the most watched YouTube video in the country during this period. BIA Against Harassment also brought an important debate to society about the offline and online harassment and gender violence women suffer.

AI Now note that addressing bias in the systems is not the same as addressing bias in society (Crawford et al., 2019): "there are some contexts in which 'fixing' such inaccuracies may not fix the overall problems presented by such systems – and some problems that cannot be fixed by a technical solution at all" (West et al., 2019). Howcroft & Rubery (2019) argue that if gender bias embedded into the current social order is not tackled head-on, the future world of work is likely to exacerbate gender equality gaps. Regulatory changes concerning the functionality of systems and the contexts in which they can be used is a dimension that governments must consider, but organisations must also encourage economic and cultural change for a fairer, more equal world of work.

CONCLUSION

Artificial Intelligence (AI) technologies will continue to affect women's opportunities for work, and their position, status and treatment in the workplace. This report outlines the opportunities and challenges that AI could present for the working lives of women. It does so by exploring the impact of new and emerging AI technologies on the skills employers will require, on how women look for and are hired for jobs, and on how jobs are structured through automated monitoring and oversight.

Societies and economies should prepare for the future of work by considering the influence of technology on the structure of labour markets and its impact on gender equality. Much remains unknown about how AI technologies will impact women at work. Designing and deploying novel technologies, guided by a principles-based approach and best practices will help ensure that today's gender stereotypes are not built into tomorrow's technological systems, and help close the gender gaps. Governments, industry, academia and civil society should work together. They should use a multi-stakeholder approach to design, deploy and evaluate AI technologies in the workplace and beyond to ensure transparency, accountability and oversight based on rigorous research surrounding the impacts of AI on gender.

More research is needed in this area. This should include qualitative and quantitative research on system design, functionality and, most importantly, social and cultural impact. Research can help ensure that the application of AI in the workplace does not create feedback loops that encode existing gender bias. Research can also address global disparities in knowledge about AI systems across country and regional contexts. Most research about AI focuses on the advanced economies usually in the Global North. As social and economic contexts vary by country, this lack of regional representation can exacerbate inequalities in the ethical design and deployment of AI. As the cases in this report show, there are real-world lessons about the benefits and harms to human rights and sustainable development from AI by focusing on its use in different global contexts.

To close gender gaps, women require equal opportunity to access the resources, training and skills they need to thrive in the workplace of tomorrow. That means access to education, re-skilling and upskilling for the jobs of the future. Societies should continue to support women entering science, technology, engineering and mathematics (STEM) and AI jobs and strive to close the gender gaps in these fields. Connectivity and access to data will be crucial job requirements in the future, especially as employees increasingly work in digital and AI-driven environments. However, research shows that gendered gaps in how workers can access digital resources remain. Women should have the ability to implement, utilise and manage AI and other technological systems.

This report reveals that the development and deployment of AI systems could have varying impacts on the working lives of women. Technological advances bring productivity gains, but for these gains to be fulfilled, talent must be developed for all individuals, regardless of gender. The design of technologies, the gendered gaps in data, and the speed, scope and scale enabled by AI can all contribute to making the situation for women workers worse if there is no active attention to this issue. Preparedness for the future entails that governments, organisations and all employees – not just women – understand the challenges and opportunities that new types of AI technologies present and how to use these technologies to create fair and equitable work, advancing the civil and socio-economic rights of women.

ANNEX: ADDITIONAL RESOURCES OF PARTNER ORGANISATIONS RELATED TO GENDER AND AI

IDB - Inter-American Development Bank

- » Responsible and ethical use of AI: [fAIr LAC](#) is a partnership between the public and private sectors, civil society, academic institutions and strategic allies. It aims to influence public policy and the entrepreneurial ecosystem in the promotion of the responsible adoption of AI and decision-support systems that improve social services delivery and create development opportunities to reduce social inequality.
- » Diversity and inclusiveness: [The Gender and Diversity Division](#) promotes gender equality, development with indigenous peoples, and the inclusion of people with disabilities, Afro-descendants and the LGBTQ + population, while harnessing the talents and capacities of these groups to promote the socio-economic development of LAC countries. The Division fulfils its mission through direct and indirect investments, technical assistance, analytical work and training.
- » The economic gender gap: The [Gender Parity Taskforces](#) (abbreviated IPG in Spanish) is a high-level public-private collaboration model that seeks to support countries interested in reducing Parity the economic gender gap. The World Economic Forum (WEF) created the IPG in 2012. In 2016, the WEF partnered with the IDB to implement these initiatives in Latin America. IPGs currently operate in Argentina, Chile and Panama, and are under development in Colombia and Peru. The IPGs seek to identify and reduce the barriers that prevent women from accessing job opportunities on equal terms.
- » Civic and political participation of women: [Program to Support the Leadership and Representation of Women \(PROLEAD\)](#) is an IDB initiative to promote the civic and political participation of women in LAC. The program seeks to increase women's access to decision-making positions and their effectiveness in power to strengthen democratic processes and institutions in the region.
- » Data and publications on women and AI the labour market: The IDB provides a [wealth of data](#) for LAC countries, including reports on women and the labour market as well as on the impact of AI on the labour market. Recent reports on these topics include [Responsible and Widespread Adoption of Artificial Intelligence in Latin America and the Caribbean](#) (2020) from fAIr LAC; [The Future of Work in Latin America and the Caribbean: What will the Labor Market Be Like for Women?](#) (2019); [The Future is Now: Transversal Skills in Latin America and the Caribbean in the 21st Century](#) (2019); [¿Desigualdades en el mundo digital?: Brechas de género en el uso de las TIC](#) (2020); [How Digitalization Can Transform Health, Education and Work as Latin America and the Caribbean Emerge from the Pandemic](#) (2021); and [Closing Gender Gaps in the World of Work](#) (2021).

OECD – Organisation for Economic Co-operation and Development

- » Data on gender and AI, and national AI policies: The OECD.AI Policy Observatory measures and monitors progress towards trustworthy AI based on implementation of the OECD AI Principles. It provides policymakers with timely data in key areas, including women's participation in [AI research](#) and [AI skills prevalence by gender](#). OECD.AI also includes a database of national AI policies and strategies, which was developed jointly by the European Commission and the OECD. This tool currently contains over 700 AI policies from over 60 countries and territories, including [initiatives](#) with mention of women and AI, providing insights into varied policy approaches.
- » AI impact on the labour market, skills and social policy: The OECD programme, with the support of Germany, on AI in Work, Innovation, Productivity and Skills (AI-WIPS) analyses the impact of AI on the labour market, skills and social policy. It produces in-depth analyses, measurement, opportunities for international dialogue and policy assessments on how AI impacts labour markets and societies, including women and underrepresented groups. Through collaboration with international policy, research, business, labour and civil society representatives, the OECD identifies necessary reforms to employment, skills and social policy. The AI-WIPS benefits from synergies with the wider programme of work and policy communities that make up the OECD.AI Policy Observatory. Some of its outputs – such as [Automation, Skills Use and Training](#) and [AI and the Future of Skills, Volume 1](#) – analyse the impacts of AI on jobs and skills for different societal groups, including women.
- » AI policy, human rights and the Sustainable Development Goals (SDGs): A coalition of eight intergovernmental and regional organisations with complementary mandates (including the IDB, OECD and UNESCO) launched [Globalpolicy.ai](#) – an online platform that aggregates work on international AI policy to create a one-stop shop for policy experts and the wider public. It acts as a forum for international collaboration on human rights and democracy, including in support of SDG 5 on Gender Equality and Women's Empowerment.
- » Studies and indicators of gender inequality: The [OECD Gender Initiative](#) examines barriers to gender equality in education, employment and entrepreneurship. It monitors the progress made by governments to promote gender equality in both OECD and non- OECD countries and provides good practices based on analytical tools and reliable data. The [OECD Gender Data Portal](#) includes indicators that shed light on gender inequalities in education, employment, entrepreneurship, health, development and governance, showing the distance to achieving gender equality and where action is needed most. The data cover OECD member countries and partner economies including Brazil, China, India, Indonesia and South Africa.
- » Reports on the digital gender divide: The OECD authored multiple reports that focus on the digital gender divide, including [Bridging the Digital Gender Divide](#) (OECD, 2018a) and [The Role of Education and Skills in Bridging the Digital Gender Divide](#) (OECD, 2019d).
- » Events on gender and AI: The OECD works with partners to raise awareness and spark dialogue on gender bias in AI. In March 2021, the OECD hosted a webinar on [Addressing the Gender Bias in Artificial Intelligence Data](#). It brought together technical and policy experts to address questions around gender bias in AI and how implementing the OECD AI Principles can help.

UNESCO – United Nations Educational, Scientific and Cultural Organization

- » Research on AI and gender: UNESCO fosters human-rights based and ethical AI development by contributing cutting-edge research and undertaking foresight research on emerging trends in the field of AI. Highlighting issues like the gender digital divide and algorithmic bias, recent publications include: *I'd Blush If I Could: Closing Gender Divides in Digital Skills through Education* (2019), *Steering AI and Advanced ICTs for Knowledge Societies* (2019) and *Letting the Sun Shine In: Transparency and Accountability in the Digital Age* (2021).
- » Recommendation on the ethics of AI: The UNESCO Recommendation on the Ethics of AI includes gender equality as a policy area and urges Member States to ensure that the potential for digital technologies and artificial intelligence to contribute to gender equality is maximised, and that the human rights and fundamental freedoms of both women and men, as well as of girls and boys, and that their safety and integrity are not violated at any stage of the AI system lifecycle.
- » UNESCO global priorities on Africa and Gender Equality: UNESCO launched the Africa Needs Assessment Survey (2020) to hear from Member States on the policy advice and capacity building needs of countries in Africa. The findings based on input from 32 countries showed a need to address gender equality-related concerns in the development and use of AI in the Global South, such as enhancing participation of women of all ages in AI education and training programs. The survey findings are used by UNESCO and international and regional partners to support African countries.
- » Raising awareness about AI and gender equality: As the development and use of AI expands, there is an urgent need to educate the public and empower them with tools to safeguard their rights. UNESCO's advocacy work includes events like *Girl Trouble: Breaking Through the Bias in AI*, a 2021 roundtable of leading voices in tech confronting deep-rooted gender imbalances, and publications such as *The AI Comic Strip* (2022), a new approach to educating the public about the lack of women's representation in the tech sector and about algorithmic bias in an engaging and accessible way.
- » Membership in the EQUALS Global Partnership: The [EQUALS Global Partnership for Gender Equality in the Digital Age](#) comprises corporate leaders, governments, businesses, not-for-profit organisations, academic institutions, NGOs and community groups around the world. All are dedicated to promoting gender balance in the technology sector by championing equality of access, skills development and career opportunities for women and men alike.

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The Effects of AI on the Working Lives of Women

The development and use of Artificial Intelligence (AI) continue to expand opportunities for the achievement of the 17 United Nations Sustainable Development Goals (SDGs), including gender equality.

Taking a closer look at the intersection of gender and technology, this collaboration between UNESCO, the Inter-American Development Bank (IDB) and the Organisation for Economic Co-operation and Development (OECD) examines the effects of AI on the working lives of women.

This report describes the challenges and opportunities presented by the use of emerging technology such as AI from a gender perspective. The report highlights the need for more focus and research on the impacts of AI on women and the digital gender gap, in order to ensure that women are not left behind in the future of work.



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