Università Bocconi
CARLO F. DONDENA CENTRE
AXA Research Lab
on Gender Equality

Threat or opportunity? The impact of AI on women

Kenza Elass and Paola Profeta

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Bocconi University

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Executive Summary

The expansion and decreasing costs of artificial intelligence (AI) have transformed our daily and professional lives. A critical question is how gender equality - a persistent dimension of inequality in modern economies and societies - will be influenced by the AI revolution.
This paper compiles existing research and analyses to explore this issue, focusing on **gender equality** in the **labor market**. It examines the various channels through which AI may act as either a threat or an opportunity for gender equality. By monitoring the evolution of these factors, we can better assess whether AI's transformation will ultimately support gender-neutral outcomes. However, reaching a definitive answer will require further, targeted research.

The channels through which AI can impact **gender equality** in the labor market include the following:

Productivity. AI has the potential to improve labour productivity growth of men and women by between 0.125 and 1.5 percentage points (Bick et al., 2024; Hatzius, 2023).

- AI helps to optimize workflows, automate repetitive tasks, and allow more focus on creative and analytical work. This can contribute to closing gender-based productivity gaps, particularly in sectors where disparities exist.
- In daily life, AI-driven tools can assist with home-related activities, potentially alleviating household burdens and fostering a more balanced division of labor, as time spent on domestic tasks is traditionally higher for women.
- However, if women have less access to or lower proficiency in AI-related skills and tools compared to men, this could widen existing gender gaps. Ensuring equal access to AI education and resources will be crucial to prevent these disparities from growing.

Labor demand. AI is reshaping the nature of jobs and the demand for some occupations, which will influence the employment and unemployment rates across different sectors. Some occupations will be replaced, as 18% of jobs could be automated by AI according to Hatzius (2023). As men and women are segregated into different jobs, they can be differently affected by AI. However, the direction of the effect is unclear.

- Roles such as managers and professionals—often male-dominated—are likely to be significantly affected by AI, as automation and advanced analytics reshape decision-making processes.

[1] *We thank Giovanni Colombo for excellent research assistance.*

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- Men are more likely to work in technical jobs with high exposure to AI, while women are more prevalent in the care sector that is less exposed to AI.
- Preliminary results suggest that women work more in occupations less impacted by AI, as men represent 57% of the total workforce exposed to AI across all country-occupations (Lane, 2024).

Job creation. AI has the potential to create new jobs and tasks, which will shape the labor market's future dynamics.

- Many of these new roles, such as AI specialists, coding experts, data scientists and various scientific positions, are expected to be male-dominated, as the current AI talent pool is mainly male.
- AI's limitations in social skills and emotional intelligence may create demand for roles where human interaction, empathy and communication are crucial. These aspects prevail in female-dominated occupations such as healthcare, education and counselling.

Hiring process. AI in recruitment can improve efficiency, particularly in high-volume hiring, by quickly screening and selecting candidates. However, there are concerns about fairness.

- AI has the potential to be less biased than human recruiters, which may help reduce gender gaps in candidates' probability of being interviewed, particularly for gender-neutral jobs.
  AI can reinforce gender stereotypes. For example, responses to prompts like "Describe a typical CEO" never refer to a woman. In AI-generated resumes, women were assigned on average almost 1 year less of experience with respect to men, particularly with respect to white men (Armstrong et al., 2024). Our research on AI-generated CVs reveals that AI often emphasizes professionalism and flexibility for men, while highlighting non-promotable tasks for women. These biases could perpetuate stereotypes in the recruitment process, underscoring the need for careful design and oversight of AI recruitment tools.

Careers and wages. AI will affect careers and wages of men and women.

- The gender gap starts at the educational stage. Women generally use less frequently AI (17.2 p.p gender gap (Carvajal et al., 2024)) and they have less AI skills, which are required in several jobs. The job segregation by gender will increase unless appropriate trainings are provided.
- Jobs with a high use of AI, such as data scientists and machine learning experts are highly male-dominated and highly paid. If women are underrepresented in these jobs the gender wage gap may further widen.

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Insights from the **health** sector are drawn highlighting two crucial directions of the impact of AI:

- **Increasing Desirable Bias**: AI can account for differences between groups, leading to more accurate and personalized diagnostic and treatment plans. By recognizing variations in health outcomes based on factors such as gender, age, or ethnicity, AI can enhance the effectiveness of medical interventions.

- **Avoiding Undesirable Bias**: It is crucial to prevent algorithms from being developed based on insufficient or skewed evidence, as this could lead to discriminatory practices in healthcare. Ensuring that AI systems are trained on comprehensive and representative data is essential to avoid perpetuating existing health disparities.

Since AI algorithms may reproduce biases leading to discrimination and specifically to gender discrimination, the paper discusses several **ethical** concerns:

- **Fairness and Transparency:** Stakeholders should be able to understand how decisions are made, particularly in areas like hiring, where bias can have significant consequences.
- **Consent:** The issue of informed consent is critical, especially when personal data is used to train AI systems.
- **Data Privacy and Security:** Ensuring data privacy and security measures is essential to protect individuals and to build trust in AI technologies.

Finally, the paper provides **recommendations** to address gender-related challenges in AI:

- **Promote Research with a Gender Lens:** There is a need for more research focused on the adoption and impact of AI through a gender perspective. This will help to identify specific challenges and opportunities for advancing gender equality in the AI landscape.
- **Develop Gender-Neutral Algorithms and AI Tools:** Efforts should be made to create algorithms and AI tools that are gender-neutral. Increasing diversity within data science teams and ensuring the production of diverse and representative datasets can contribute to achieving this goal.
- **Implement Gender-Inclusive Training Programs:** Promoting gender-inclusive training programs will equip both men and women with the necessary skills to equally participate in the AI transformation.

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1. Introduction

Although Artificial Intelligence (AI) is not a recent innovation, its recent accessibility, driven by the release of OpenAI's ChatGPT, has deeply transformed both our daily and professional lives. Indeed, AI, which can be defined as "a *machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments*" (UNESCO, 2022), is commonly used by 40% of the working-age US population (Bick et al., 2024). Figure 1 shows the Google Trend Interests over time for ChatGPT, the most famous generative AI tool. The figure shows that ChatGPT continues to gain popularity.

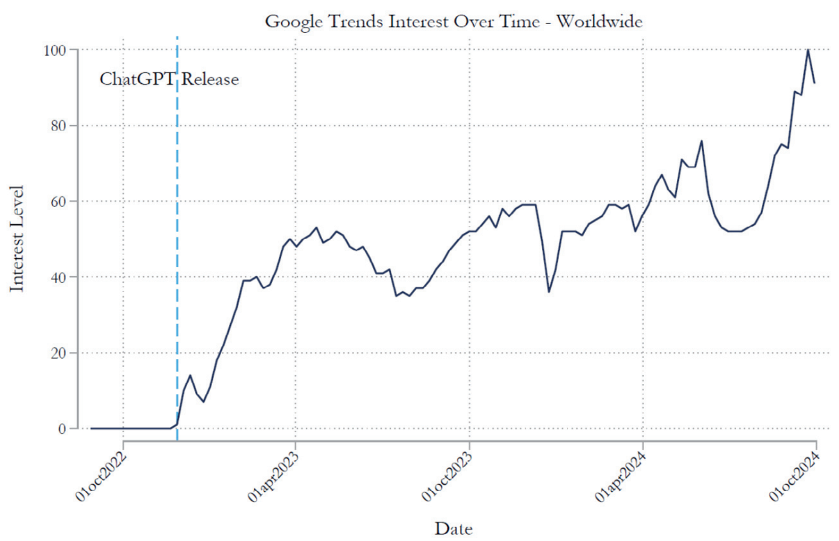

Figure 1: Google Trend Interests -"ChatGPT"
Source: https://trends.google.com/trends/explore?date=2022-09-01%202024-10-1&q=chatgpt&hl=en

A critical question is how **gender equality**—a persistent dimension of inequality in modern economies and societies—will be influenced by the AI revolution. This paper examines existing research and analyses to explore this issue, focusing on gender equality in the **labor market**. In fact, AI will have profound consequences on labor market dynamics: it is reshaping the nature of work, by reallocating routine tasks from humans to machines, it is changing job roles, skill requirements, and the overall demand for labor (OECD, 2018; Deloitte AI Institute, 2024). AI, offering a cost-effective alternative, raises the concern of reducing employment demand in certain occupations, thus increasing unemployment among workers in the affected fields. However, the impact of AI on gender gaps in employment remains uncertain: the paper will explain why AI may act as either **a threat or an opportunity** for gender equality.

[2] *kenza.elass@unibocconi.it, paola.profeta@unibocconi.it.*
We thank Giovanni Colombo for excellent research assistance.

1. Introduction

Gender gaps in the labor market remain significant worldwide. According to the World Economic Forum, as of 2024 no country in the world has achieved gender equality, with the economic dimension being particularly crucial. If AI has the potential to reduce gender gaps in the labor market, it would represent a significant advancement. If instead it exacerbates existing gender gaps, it presents a serious challenge. To assess the potential impact of AI on gender gaps in the labor market we start from well known dynamics in the labor market.

A crucial role is played by occupational segregation. Men and women work in separate occupations, fields, roles and sectors (See Figure 2). This segregation depends on educational choices, social norms, public policies and discrimination, which have been largely studied by the economic literature (see Profeta, 2020 for a review). Understanding how AI interacts with these dynamics is essential for assessing its overall impact on gender equality in the workforce. Section 2.1 details the AI's impact on the gender gap in the labor market, focusing on p**roductivity, labor demand** and replacement across sectors, roles and jobs and **creation of new jobs** and tasks.

When we consider productivity, three important results emerge, pointing to different directions. First, AI helps to optimize workflows, automate repetitive tasks, and allow more focus on creative and analytical work. This can contribute to closing gender-based productivity gaps, particularly in sectors where disparities exist. Second, in daily life, AI-driven tools can assist with home-related activities, potentially alleviating household burdens and fostering a more balanced division of labor, as time spent on domestic tasks is traditionally higher for women. Third, if women have less access to or lower proficiency in AI-related skills and tools compared to men, this could widen existing gender gaps.

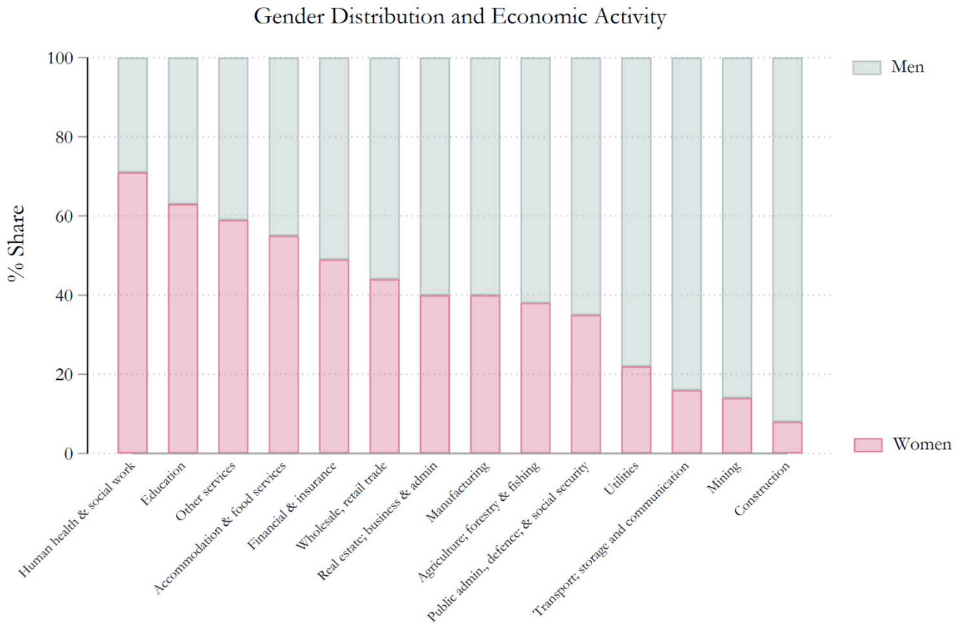

Figure 2: Share of employed women and men by sector of occupation, 2021

Note: Economic activity is classified using the International Standard Industrial Classification of All Economic Activities, revision 4 (ISIC rev 4). Category "Other services" aggregate workers from categories R, S, T and U of ISIC rev 4, corresponding respectively to "Arts, entertainment and recreation" (R), "Other service activities" (S), "Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use" (T), and "Activities of extraterritorial organizations and bodies" (U).
Source: OECD (2023), "Gender-based occupational segregation remains substantial: Share of employed women and men by sector of occupation, 2021", in SIGI 2023 Global Report: Gender Equality in Times of Crisis, Social Institutions and Gender Index, OECD.
Publishing, Paris, https://doi.org/10.1787/ca8eded6-en. (ILO, 2021[73]), "World: Employment by sex and economic activity - ILO modelled estimates, Nov. 2022 (thousands)", Statistics on employment, ILOSTAT, https://www.ilo.org/shinyapps/bulkexplorer45/?id=X01_A&indicator=EMP_2EMP_SEX_ECO_NB.

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Moving to labor demand, the effects of AI on gender gaps are unclear. Roles such as managers and professionals—often male-dominated—are likely to be significantly affected by AI, as automation and advanced analytics reshape decision-making processes. However, middle-skill jobs in services and retail, which are female-dominated sectors, may see greater disruption as AI is increasingly applied to customer service, sales, and other routine tasks. Moreover, research suggests that men are more likely to work in technical jobs with high exposure to AI, while women are more prevalent in the care sector that is less exposed to AI. Our preliminary analysis on new data suggests that women work more in occupation less impacted by AI.

New jobs will be created by AI. On one hand, many of these new roles, such as AI specialists, coding experts, data scientists and various scientific positions, are expected to be male-dominated, as the current AI talent pool is mainly male. On the other hand, AI's limitations in social skills and emotional intelligence may create demand for roles where human interaction, empathy and communication are crucial. These aspects prevail in female-dominated occupations such as healthcare, education and counseling.

In Section 2.2 we concentrate on the **hiring process**. AI in recruitment can improve efficiency, especially in high-volume hiring, by quickly screening and selecting candidates. However, there are concerns about positive or negative effects of AI on discrimination during hiring, and stereotypes in recommendations to job seekers. Since generative AI usage is more common among more educated and higher-income workers (Bick et al., 2024), AI leveraged to improve decision-making processes could either amplify or alleviate gender discrimination in hiring. AI has the potential to be less biased than human recruiters, which may help reduce gender gaps in candidates' probability of being interviewed, particularly for gender-neutral jobs. However, AI can even reinforce gender stereotypes. For example, responses to prompts like "Describe a typical CEO" never refer to a woman!

In Section 2.3 we consider how AI may influence gender disparities across different **career development stages** and the **gender wage gap**. The gap starts at the **educational** level, where differences in access to resources and opportunities can lead to unequal skill acquisition. This initial disparity can widen as individuals progress through the labor market and develop their careers.

A first step is the access to internet. Figure 3 shows gender disparities in the use of internet. The figure indicates that, in most Western countries, the gender gap in internet use either benefits women or is negligible. However equal access to the internet does not necessarily translate into an equal use of AI tools. In fact, Figure 4 shows that, for example, women use ChatGPT significantly less than men. Moreover, Figure 5 shows that in every country with available data, a gender gap in coding exists among individuals aged 16 to 24. This gap is particularly pronounced in Europe and Canada, reaching up to 20 percentage points. AI tools like ChatGPT are being adopted unevenly across genders and generations, which could lead to disparities in opportunity during the career, especially in terms of wages. Jobs with a high use of AI and coding, such as data scientists and machine learning experts are highly male-dominated and highly paid. If women lack these skills and are underrepresented in these jobs, the gender wage gap may further widen.

The trends reported in Figures 4 and 5 are confirmed by recent research. Humlum and Vestergaard (2024) conduct a survey experiment in Denmark and find that women are 20 percentage points less likely to use ChatGPT than men, in the same occupation. This result stems from larger adoption barriers, rather than from differences in beliefs regarding the productivity of ChatGPT. Similarly, the survey conducted by Carvajal et al. (2024) shows that female students are less likely to use ChatGPT and less skilled to write successful prompts.

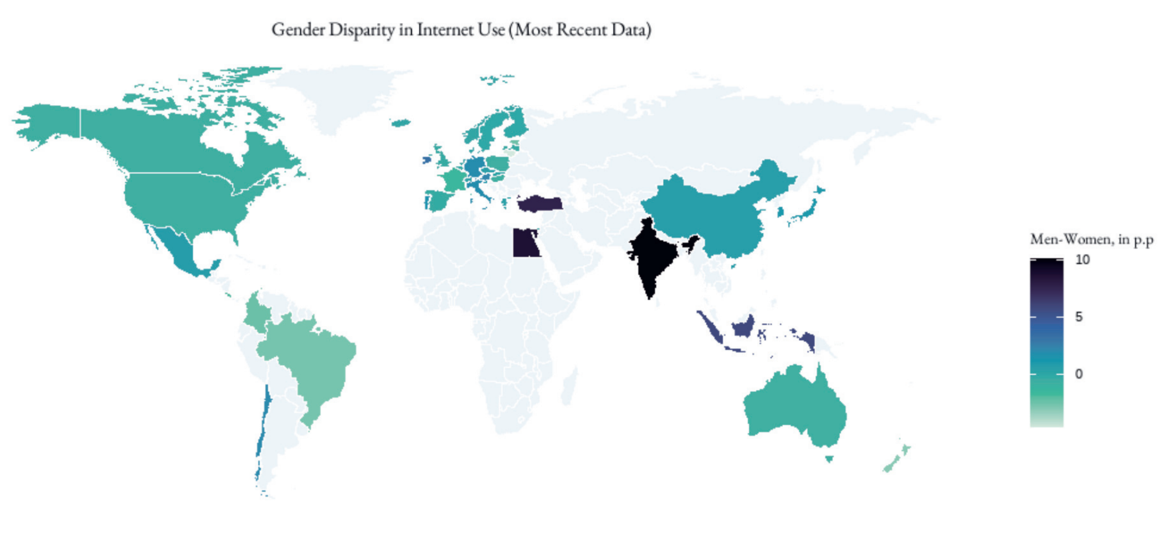

Figure 3: Map of gender disparity in Internet use in p.p
Source: The OECD Going Digital Toolkit, based on the OECD ICT Access and Usage by Households and Individuals Database, https://oe.cd/dx/ict-access-usage, and the ITU World Telecommunication/ICT Indicators Database.

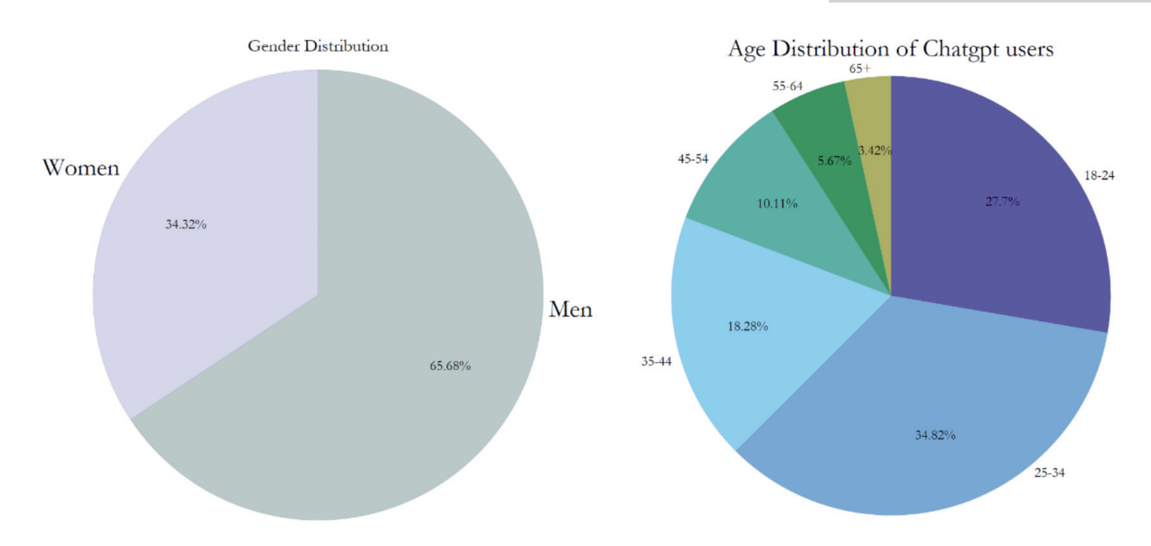

Figure 4: Descriptive statistics of ChatGPT users - Age and Gender
Source: Enterpriseappstoday.com

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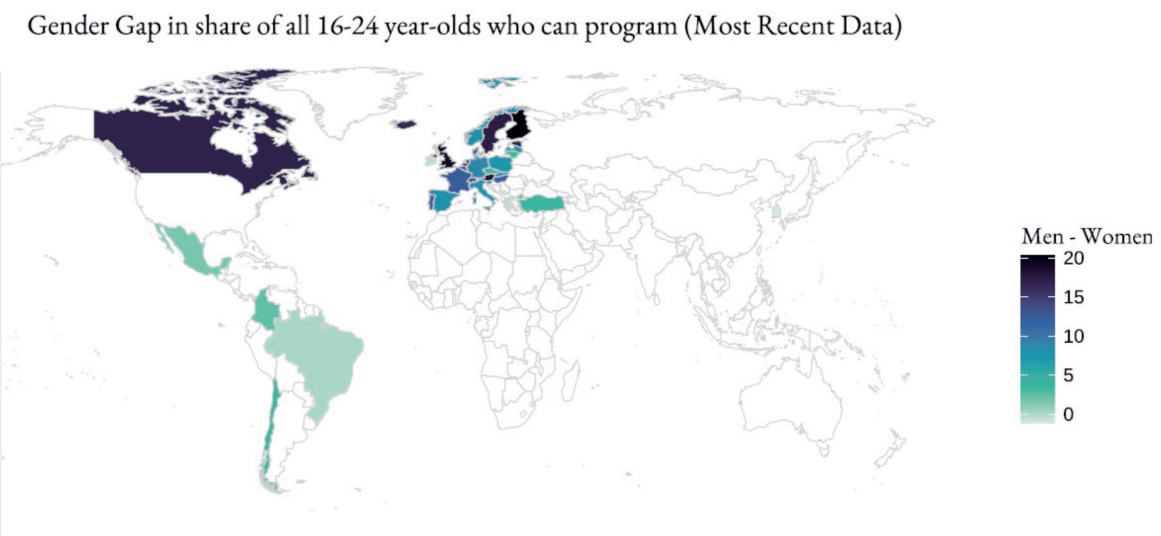

Figure 5: Map of Gender Gap in 16-24 who can program
Source: The OECD Going Digital Toolkit, based on the OECD ICT Access and Usage by Households and Individuals Database, https://oe.cd/dx/ict-access-usage.

Section 3 presents insights on AI and gender gaps from the health sector. The rise of AI in the **health sector** offers transformative potential, yet it also raises important ethical concerns, particularly regarding gender equality. In Section 3 we discuss how AI systems can be used to improve effectiveness of medical interventions, by accounting for differences between groups, while, at the same time, being trained on input data, they can unintentionally perpetuate existing biases, especially with better knowledge of the male body, leading to unequal health outcomes.

Overall, the adoption of AI raises **ethical concerns** around the fairness and transparency of AI decision-making, particularly related to treatment of data, privacy and security. We briefly address these issues in Section 4.

Finally, in Section 5 we provide **recommendations** to address gender-related challenges in the context of AI. We encourage research with a gender lens, we recommend the adoption of gender-neutral algorithms and AI tools and we encourage the implementation of gender-inclusive training programs, which should be designed to bridge the existing skills gap and reinforce the presence of women in AI workforce. It is essential to ensure that both men and women are represented in AI design and research teams. Diversity in these teams can lead to more equitable and comprehensive AI solutions, ultimately contributing to a more inclusive AI landscape.

2. Labor Market

2.1 Employment demand

Generative AI has been adopted faster than computers or the internet, mainly because of the differences in portability and cost (Bick et al., 2024). As a result, AI may reshape supply and demand in the labor market, affecting the gender gap at work.

First, one of the most highly anticipated and expected impacts of AI is the one on **productivity**. AI may bring some benefits in terms of economic growth (Hatzius, 2023; Brynjolfsson et al., 2018), and productivity through the reduction of costs and the creation of new opportunities for innovation (Bohren et al., 2023; Bick et al., 2024), also impacting the allocation of tasks to capital and labor (Acemoglu and Restrepo, 2019). Although the literature has not yet explored a gendered impact of AI on the overall productivity of workers, Bohren et al. (2023) document that competition with generative AI negatively impacts the creativity of female participants, while it is not the case for men, consistently with the documented competition-shy behavior of women.

Regarding **employment**, a major concern is about the jobs and industries potentially being replaced by AI and the resulting unemployment (Zarifhonarvar, 2024). The developing countries seem to exhibit lower exposure levels than advanced economies due to the different employment compositions. Furthermore, high-skill occupations such as professionals and managers are more exposed to AI due to the high concentration of cognitive-based tasks (Pizzinelli et al., 2023; Hatzius, 2023). However, the literature documenting whether male or female jobs and industries are more impacted by AI is pretty scarce. Shen and Zhang's (2024) findings in China do not demonstrate a heterogeneous effect on the gender structure of employment. Furthermore, while Pizzinelli et al. (2023)'s results in a cross-country analysis show that women are more exposed to AI than men, primarily due to their predominant employment in middle-skill service and retail occupations, Webb (2019) findings suggest the inverse, as men are more likely to work in technical jobs exposed to AI, rather than jobs in the care sector, less exposed. We have conducted an analysis for the French economy, using the index of AI-exposed occupations built by Webb (2024) and the share of women in the occupation using French Administrative data (2009-2019) (BTS data). Preliminary results, which are shown in Figure 6, suggest that women work in occupations less impacted by AI.

These contradictory findings, with different measures, contexts, and estimation strategies, highlight the necessity for more analysis focusing on this question.

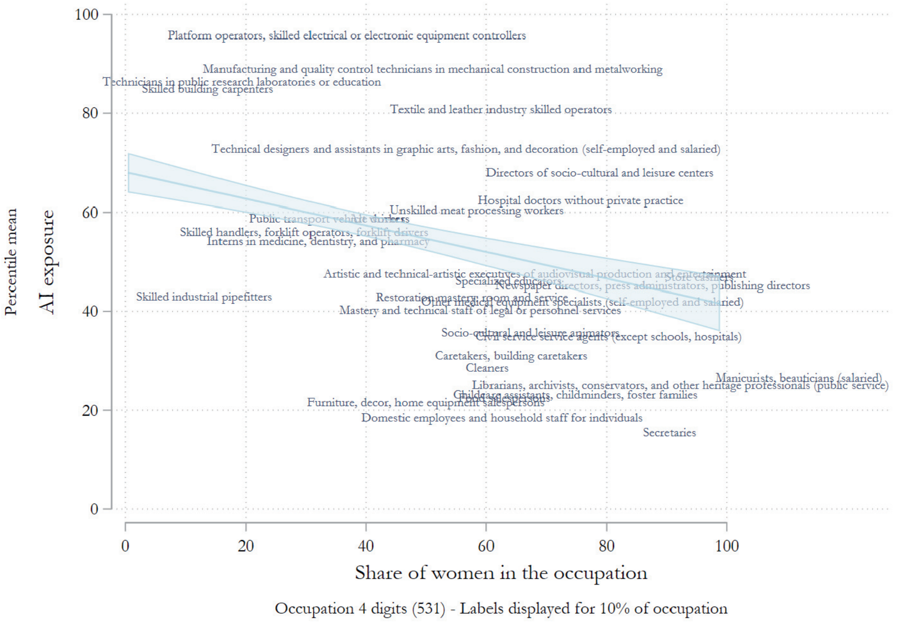

Figure 6: Gender composition of AI exposed occupations

Source: Kenza Elass, Fabien Petit, Paola Profeta (2024) using the Index of AI-exposed occupations built by Webb (2024) and the share of women in the occupation using French Administrative data (2009-2019) (BTS data).

Another aspect of the impact of AI on employment relates to the **job creation**. Indeed, not only AI could benefit employment through complementation and productivity increase but also via employment development. While the evidence in the economic literature is still mixed, AI could also have a positive effect on employment through the creation of new jobs and new tasks, rather than reducing labor demand (Brynjolfsson et al., 2018; UNESCO, 2022; Hatzius, 2023). This "*employment compensation*" theory, highlights the new products, models, and industrial sectors induced by the progress of AI technology (Shen and Zhang, 2024). On the one hand, data analysts and more scientific occupations are required to carry on the development and monitoring of these new technologies (Lane and Saint-Martin, 2021; Acemoglu et al., 2022). However, these newly created jobs are likely to be male-dominated, as suggested by Figure 7, showing that in every industry, AI talents are mainly men.

Figure 7: Gender share of AI talent

Source: LinkedIn Economic Graph Research Institute. Notes: This chart displays the proportion of AI talent, with AI engineering skills, by gender per industry, globally for 2023. A LinkedIn member is considered an AI talent if they are occupied in an AI occupation. The global average of female AI talent with AI engineering skills in 2023 is denoted by the grey line.

On the other hand, AI lacks managerial and social skills as well as emotional intelligence, prevailing in female-dominated occupations (Su et al., 2021; Weidinger et al., 2021). AI's limitations in social skills and emotional intelligence may create demand for roles where human interaction, empathy and communication are crucial. These aspects prevail in female-dominated occupations such as healthcare, education and counselling. Hence, it is uncertain whether created jobs will benefit men or women.

Overall, the emergence of these new jobs created by AI may not be equally accessible to men and women, due to existing educational disparities, access to training programs, and gender norms that may disadvantage women wanting to switch towards these high-demand fields (Lane and Saint-Martin, 2021).

2.2 Hiring

A key aspect of the labor market that can be directly influenced by the availability of low-cost AI is the recruitment process. Integrating generative AI into the CV screening process may considerably improve efficiency over traditional manual methods, particularly in high-volume recruitment scenarios. Indeed, AI may help identify relevant information but also exclude personal data (Gan et al., 2024). An important dimension of the recruitment process to consider is the fairness of the hiring decision. While AI might be less biased than human recruiters, job-seekers' perceptions of fairness could also influence their self-selection behavior. Indeed, job-seekers may perceive automatic decision-making as fairer than human decision-making, in terms of both procedural (whether the selection procedure is deemed as fair) and distributive fairness (whether the selection output is deemed as fair) (Marcinkowski et al., 2020). Hence, the introduction of automated resume screening as a substitute for human recruiters may lead to a reduction in the gender gap in candidates' probability of being interviewed for a gender-neutral job. Avery et al. (2023) conduct two field experiments and show that first, the use of AI reduces the gender gap in application completion rates. Second, on the demand side, correspondence studies with identical resumes show that AI is more likely to provide smaller resume scores for women (Armstrong et al., 2024; Bai et al., 2024; Lippens, 2024). However, AI seems to be less biased than human recruiters, and the bias is removed when human evaluators are given scores computed by AI (Avery et al., 2023). Similar results are found by Pisanelli (2022), who show that automated resume screening leads to reduced gender discrimination. Likewise, regarding AI-driven reference letter generation, generative AI seems to be less biased against women than humans (Farlow et al., 2024).

The use of AI has not only the potential to transform recruitment by influencing bias in the screening process on the employer's side but also by reshaping the job seeker's application package. As a result, some studies have focused on AI-generated CVs. Previous research has shown that large language models are gender-biased (Zhao et al., 2024; Wan et al., 2023). As an example, Figure 8 indicates that for three different large language models, the response to the prompt "Describe a typical CEO" never refers to a woman. Among the documented male stereotypical traits, we find characteristics related to ability, standout, or leadership, while female stereotypes relate to citizenship and personality. These gender biases are reflected in CVs generated by AI, as evidenced by Armstrong et al. (2024). Analyzing resumes generated by ChatGPT, Armstrong et al. (2024) demonstrate that CVs generated for women are characterized by fewer and shorter experience and seniority, with administrative or caregiver roles. Elass et al. (2024) complement this analysis by showing that in CVs, generative AI reproduces stereotypes identified in the literature. As a result, men are more likely to be described as professional, with a highlighted temporal flexibility, while CVs generated for women emphasize non-promotable tasks. These stereotyped CVs may have important implications for wages as these characteristics reflect non-wage amenities. In addition, some studies revealed that AI can also perpetrate racial discrimination (Kirk et al., 2021; Armstrong et al., 2024; Lippens, 2024; Zack et al., 2024).

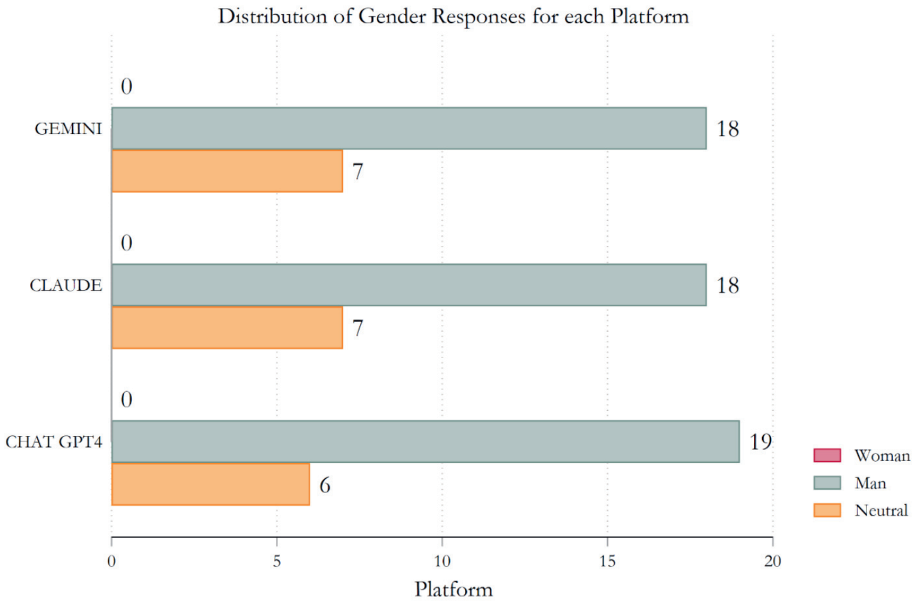

Figure 8: Distribution of gender response by generative AI model, for the prompt "Describe a typical CEO in a paragraph up to 100 words"
Source: Anjali Devrani, https://public.tableau.com/app/profile/anjali.devrani/viz/AIGender-BiasResearch/AIGenderBiasResearch

However, only a few studies have explored this topic, and additional research is necessary to better understand the multiple aspects of AI stereotypes on recommendation to job-seekers. Notably, the findings of Kotek et al. (2023) and Kirk et al. (2021), who examine how generative AI associates occupations with gender, suggest that bias in screening and CV generation may depend on the gender composition of the occupation. Hence, in a recent experiment with resume creation and scoring by generative AI, Elass et al. (2024) show that female candidates are more discriminated against in male-dominated occupations. This could be explained by the AI perpetuation of statistical discrimination based on the pre-training data. Besides, the results of Veldanda et al. (2023) indicate a dislike of AI for characteristics related to maternity or pregnancy, highlighting the need for further research in this area.

2.3 Careers and wages

The influence of AI may be reflected in the various stages of life, starting from education, but also through different uses of AI and during the career's evolution.

The stereotypes mentioned above could emerge if students ask for recommendations to AI about their studies, but to our knowledge, there is no research focusing on this question. Also, if the gender bias in AI stems from the construction of the algorithm, there is a need to increase the share of women in data science and software engineering teams.

The observed gender disparity in the use of AI tools, such as ChatGPT, raises concerns about career inequality. Indeed, women who do not acquire AI skills may be less skilled or discouraged from applying for jobs that require proficiency in these tools. This effect could be reinforced greater likelihood of women perceiving a need for training in ChatGPT (Humlum and Vestergaard, 2024). This could lead to missed opportunities for promotions and career advancement, while AI knowledge is increasingly becoming a requirement. This evidence calls for more professional training in AI tools, especially as the experiment of Humlum and Vestergaard (2024) demonstrates higher female responsiveness to expert information about the potential time saved by AI.

Another aspect that has so far received little attention due to the lack of recent and adequate data pertains to wage inequality. AI stereotypes in AI recommendations provided to job seekers could push more women toward female-dominated jobs, which are lower paid. Besides, AI could exacerbate income inequalities, since the benefits of productivity gains may accrue primarily to those who own the technology, more generally to the top quantiles of income distributions. Indeed, Figures 9 and 10 displaying the salary and gender composition of data scientists and machine learning experts, suggest that these jobs are at the top of the wage distribution, and highly male-dominated. In contrast, the first evidence suggests that AI could compress wages at the middle of the distribution but increase disparities at the top (Webb, 2019). Ultimately, the impact of AI on the gender wage gap has not been explored in the literature yet.

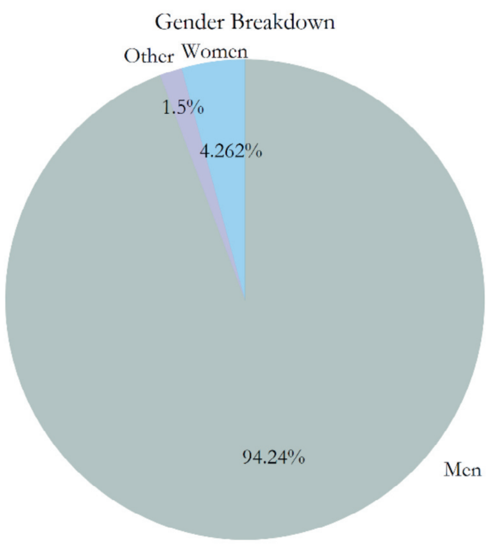

Figure 9: Gender breakdown of data scientists and machine learning experts

Source: Stackoverflow Survey, OECD.AI (2024), www.oecd.ai. Supported by the Patrick J. McGovern foundation. Notes: Aggregate demographic information from survey respondents is leveraged to build indicators and identify trends related to the profession, country, salary, education, gender, and age of AI developers.

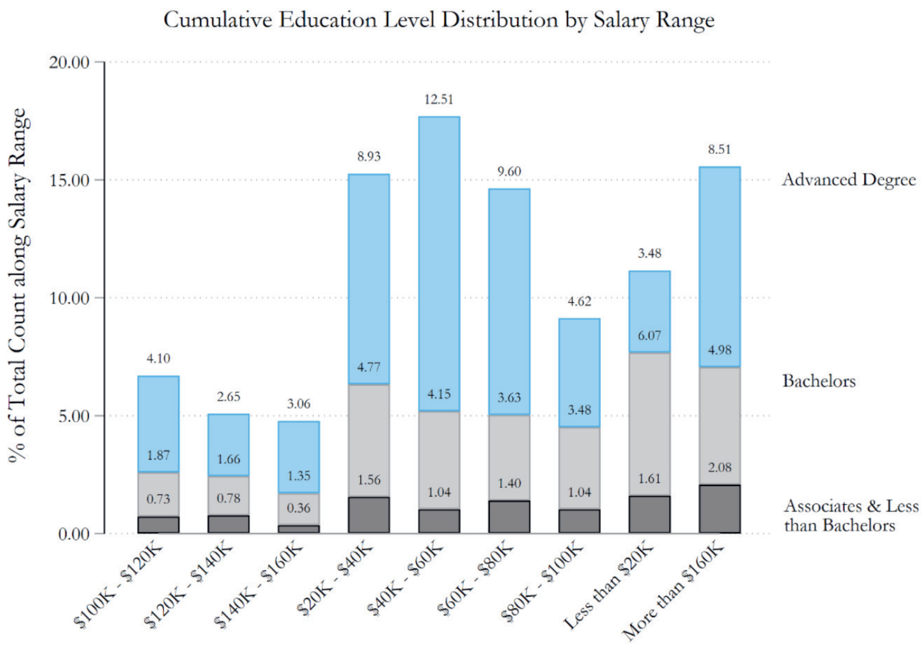

Figure 10: Salary breakdown by education level of data scientists and machine learning experts
Source: Stackoverflow Survey, OECD.AI (2024), www.oecd.ai. Supported by the Patrick J. McGovern foundation.
Notes: Aggregate demographic information from survey respondents is leveraged to build indicators and identify trends related to the profession, country, salary, education, gender, and age of AI developers.

3. Insights from the Health Sector

3.1 Gender inequality in health

Health disparities also exist between men and women. Indeed, Figure 11 showing the ratio of men to women reporting good health status illustrates that in most OECD countries, men report better health status than women, as indicated by a ratio above 1.

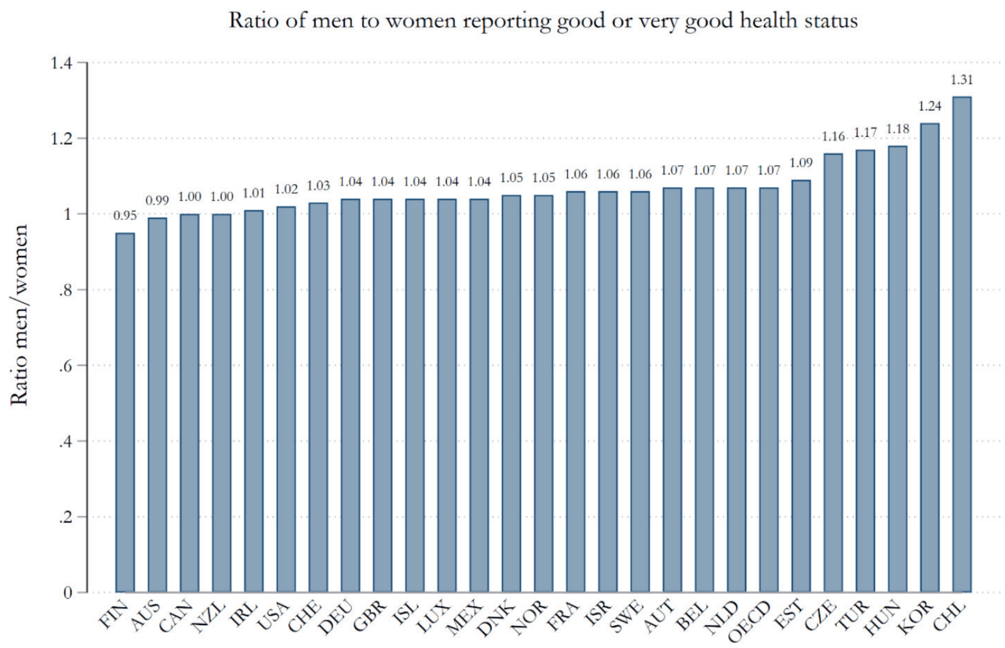

Figure 11: Gender gaps in self-reported health status

Source: European Union Statistics on Income and Living Conditions (EU-SILC) for most European countries and OECD (2013c), "OECD Health Data: Health status", OECD Health Statistics (database), http://dx.doi.org/10.1787/health-data-en. Notes: Data for 2011 or later.

Similarly, Figure 12 shows women are more likely to declare limitations in daily activities. This disparity suggests that women may face stronger health challenges or barriers. These differences could stem from discrimination in diagnostics or access to healthcare, may result from occupational segregation in the labour market or may even reflect the consequences of maternity as well as gender norms.

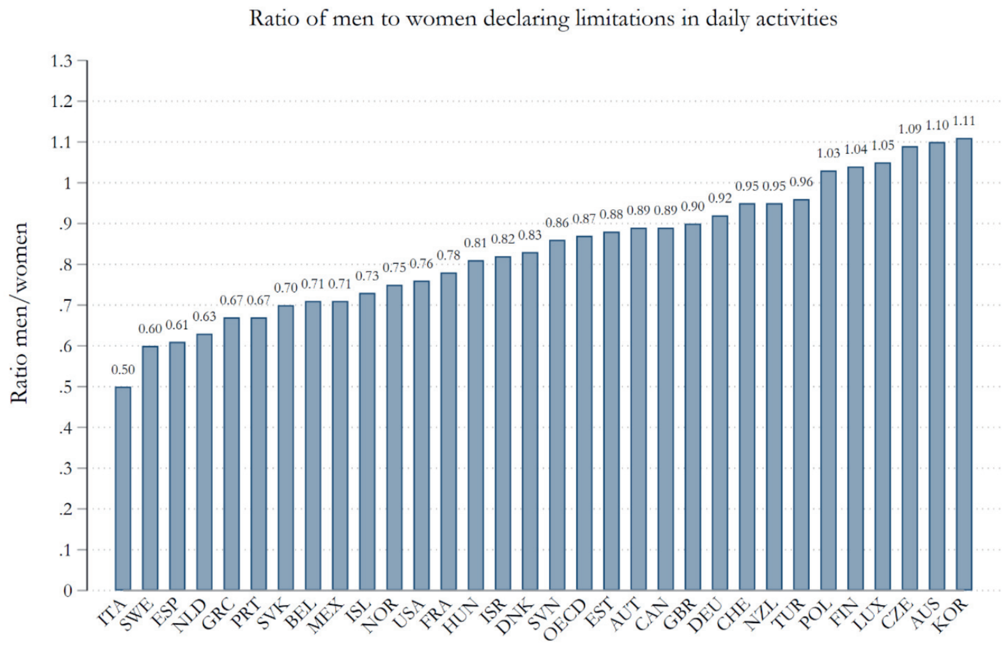

Figure 12: Gender gaps in self-reported limitations in daily activities

Source: European Union Statistics on Income and Living Conditions (EU-SILC) for most European countries and OECD's calculations based on data from the Gallup World Poll, www.gallup.com/strategicconsulting/en-us/worldpoll.aspx. OECD (2013), How's Life? 2013: Measuring Well-being, OECD Publishing, Paris, https://doi.org/10.1787/9789264201392-en. Notes: Data for 2011 or later.

Indeed, in recent years, the public debate has focused on the role of mental load and disparities in domestic work. Figure 13 illustrates this pattern since it shows that across all countries, women shoulder a greater share of unpaid work compared to men. Although the extent of this gap varies from one country to another, it remains an issue even in Western countries. These inequalities may stem from gender norms and expectations, which often give a disproportionate responsibility for caregiving and household duties to women. It is also linked with the invisible responsibility of managing everyday tasks, plans, and decisions, called the mental load, which impacts considerably mental health.

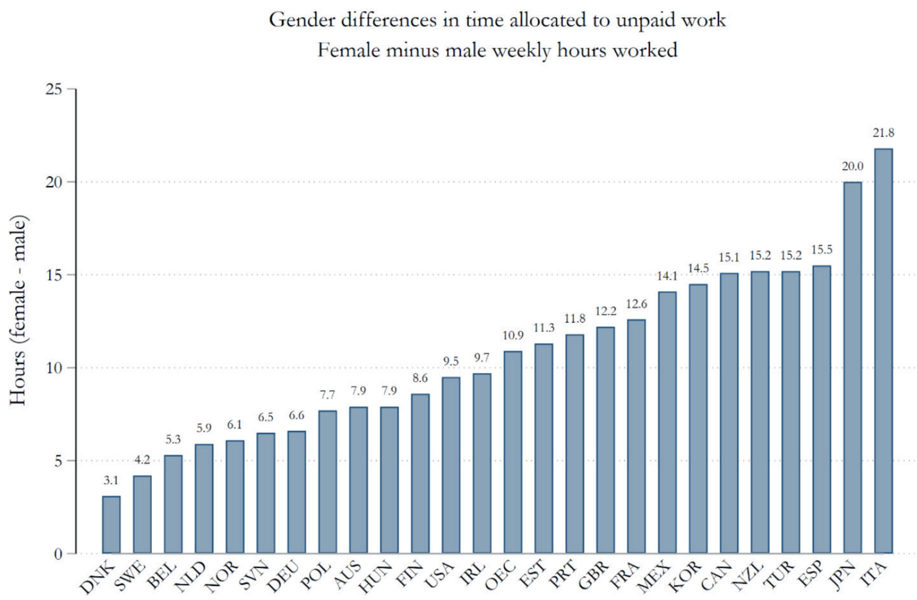

Figure 13: Gender differences in time allocated to unpaid work

Source: OECD's calculations based on national time use surveys, OECD (2013), How's Life? 2013: Measuring Well-being, OECD Publishing, Paris, https://doi.org/10.1787/9789264201392-en. Notes: Data refer to 2011 for Japan and the United States; to 2010 for Canada and Norway and to 2009-10 for Estonia, Finland, France, New Zealand and Spain. Data refer to 2009 for Korea and Mexico; to 2008-09 for Austria and Italy; and to 2008 for Turkey. Dta refer to 2006 for Australia, China, the Netherlands and Turkey; to 2005 for Belgium, Ireland and the United Kingdom; to 2003-04 for Poland; and to 2001-02 for Germany. Data refer to 2001 for Denmark; to 2000-01 for Slovenia and Sweden; to 2000 for South Africa; to 1999-2000 for Hungary; and to 1999 for India and Portugal.

Violence against women is another important aspect of this issue as it has effects on their health, both physically and psychologically. As highlighted in Figure 14, between 12 and 32% of women experience physical abuse by their partner once over a lifetime. The implications of physical abuse on physical health are obvious but it also extends beyond the visible, with psychological effects. Women who experience violence are at a higher risk of mental health disorders, including depression, anxiety and post-traumatic stress disorder. These health outcomes are often amplified by a lack of access to supportive services or healthcare.

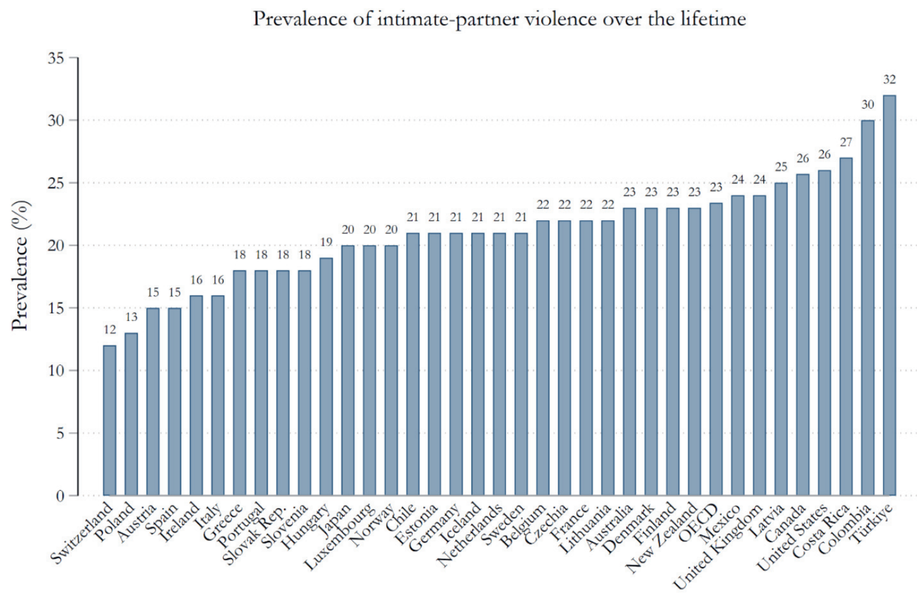

Figure 14: Violence against women

Sources: Gender, Institutions and Development Database (GID-DB) 2023 Notes: Prevalence of violence in the lifetime refers to the share of women who have experienced physical and/or sexual violence from an intimate partner at some time in their life.

3.2 AI & gender

AI programs are applied in the health sector, for example for diagnostics, medicine and protocol development, or patient monitoring. To ensure gender equity in the development of AI tools, one should address desirable bias and avoid undesirable bias (Lee et al., 2022). Desirable Biases result from accounting for differences between groups to allow for more accurate and tailored diagnostic and treatment plans. In contrast, undesirable biases occur when algorithms developed based on a lack of adequate evidence or based on skewed evidence result in discrimination (Lee et al., 2022). The findings of Chen et al. (2019) demonstrate higher error rates for female patients, with resulting differences in prediction accuracy for ICU mortality. Studies that test digital biomarkers are often performed with small sample sizes and tend to show insufficient demographic information on sex and gender, usually with an under-representation of women. Indeed, if an algorithm is trained with a dataset over-represented by male patients, it may lead to more accurate detection of male symptoms in comparison to female ones (Cirillo et al., 2020). As a result, lower performance for the underrepresented gender may appear when a minimum balance is not fulfilled, while a Computer Aided Diagnosis system trained with a diverse (and balanced) dataset achieved the best performance for both genders (Larrazabal et al., 2020).

Gender is not the only discriminatory aspect associated with AI tools in the health sector as racial bias is also a concern. Indeed, the research conducted by Zack et al. (2024) highlights that for conditions with similar prevalence by race and gender, the AI model is substantially more likely to generate cases describing white men. In addition, their results emphasize an overestimation of risk for Black women and an underestimation of Hispanic and Asian populations. Thus, GPT-4 perpetuates stereotypes about demographic groups when providing diagnostic and treatment recommendations. As a result, changing gender or race and ethnicity affected the ability of GPT-4 to correctly prioritise the top diagnosis in many cases. Furthermore, GPT-4 seems less likely to rate stress testing of high importance for female patients than for male patients.

For these reasons, the main focus should be first on the increase of the desirable bias with better representativeness of the data to ensure gender fairness in the development of AI tools for health. This could be achieved through an expansion of data collection to reflect population variability and diversity (Lee et al., 2022; Buslón et al., 2023). Second, these measures should be supported with the promotion of gender biases in AI awareness, via training and education activities targeting future professionals in STEM and health. These training programs should target better healthcare assistance and effective human-machine interactions for biomedical applications, as well as better translation of ethical decision-making into machines. (Cirillo et al., 2020; Lee et al., 2022; Buslón et al., 2023).

4. Ethical concerns

Since AI algorithms may reproduce biases leading to discrimination, this raises ethical concerns about AI's use in hiring or other types of selection processes (Cirillo et al., 2020; De- loitte AI Institute, 2023). It is necessary to conduct more research on the underlying mechanisms of Automated Decision Making and its perceived fairness in comparison with Human Decision making. Indeed, while studies comparing the fairness of AI and human decisions reveal considerable variance in various fields (e.g., justice, health, education system), the empirical findings seem to be highly context-sensitive (Marcinkowski et al., 2020; Starke et al., 2021).

In addition, Starke et al. (2021) document negative effects for institutions using an AI if perceived to be unfair, especially concerning its reputation and people's willingness to exit the institution. Besides, the use of AI in various sectors raises concerns regarding consent, data privacy and security. As a result, organizations must ensure the protection of sensitive information while leveraging AI technologies, together with transparency and potential legal challenges (UNESCO, 2022; Buslón et al., 2023; Deloitte AI Institute, 2023).

Lastly, Stevenson and Doleac (2024) focus on the impact of AI on the legal dimension. As judges exercise discretion, demographic factors, particularly race and age, play an important role in the judge's sentences. However, they show that the adoption of algorithmic risk as- assessments did not yield the anticipated benefits in terms of reducing incarceration rates or improving public safety. This suggests that the algorithmic tools may inadvertently reinforce existing disparities in the judicial system.

5. Conclusion and recommendations

The adoption of AI in various sectors has led to changes that present both opportunities and challenges for gender equality. Although AI appears to be less biased than human decision- makers, the literature also suggests it perpetuates stereotypes and inequalities between men and women. The unequal use of AI tools, combined with existing disparities in education and employment, may further disadvantage women in the labor market. In addition, AI's influence on employment, wage inequality and gender bias in healthcare has not been sufficiently studied, raising ethical questions about the fairness and transparency of these technologies.

A major challenge for gender gaps is the existence of a wide gender gap in AI skills. Figure 15 shows that men are acquiring AI skills faster than women, suggesting that men are responding more quickly to the increasing demand for AI talent, therefore increasing the gender gap over time of AI talents.

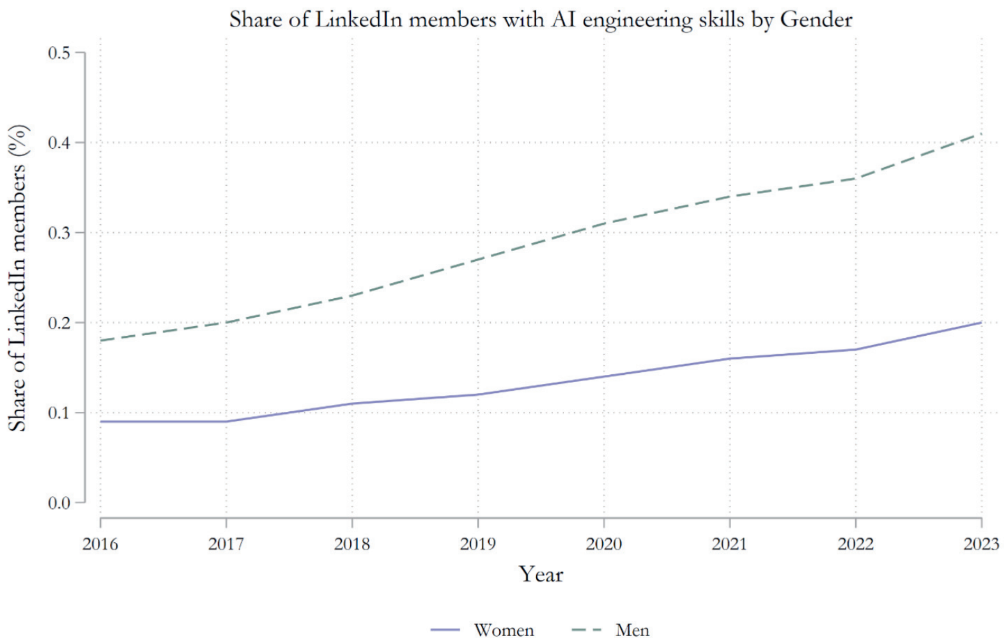

Figure 15: Share of LinkedIn members considered AI talent by gender
Source: LinkedIn Economic Graph Research Institute, OECD.AI (2024), Notes: This chart displays the share of LinkedIn members who are considered AI talents, with AI engineering skills. A LinkedIn member is considered an AI talent if they are occupied in an AI occupation.

The gap in AI skills reflects also in the scarce presence of women in AI research. Figure 16 shows that there are substantially fewer publications in AI with at least one female author.

To effectively leverage AI for reducing gender gaps, it is essential to begin with equal access to AI skills for both men and women. This foundational step ensures that AI will not increase gender gaps in the labor market. Moreover, promoting research conducted by women is crucial. By fostering a diverse research environment, we can ensure that the development and application of AI tools are inclusive and considerate of the perspectives and needs of men and women. Ultimately, addressing these areas will be vital in creating a more equitable landscape in which AI can serve as a tool for closing gender disparities.

5. Conclusion and recommendations

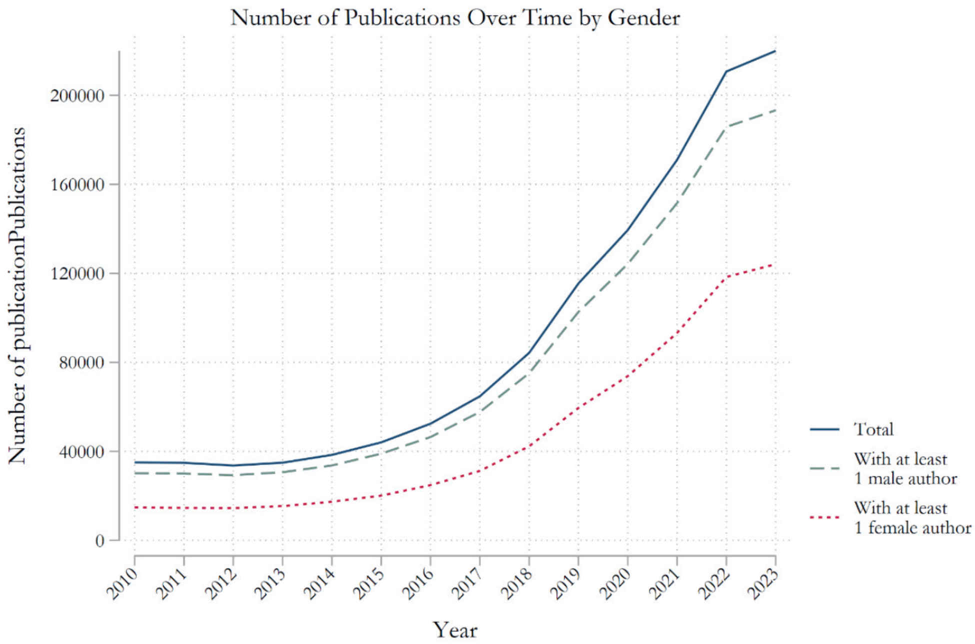

Figure 16: Number of research publications in AI
Source: https://Scopus.com, using data from Elsevier, accessed on 27/10/2024, www.oecd.ai, OECD.AI (2024), Notes: For this experimental indicator, Elsevier assigned a gender value only to those authors in the Scopus dataset for whom the algorithm used returned a gender probability of 85% or higher. To ensure a sufficient number of authors for analysis, the gender probability threshold was set at 70% for China.

Our analysis suggests the following recommendations:

Promote Research with a Gender Lens: There is a need for more research focused on the adoption and impact of AI through a gender perspective. This will help to identify specific challenges and opportunities for advancing gender equality in the AI landscape.

Develop Gender-Neutral Algorithms and AI Tools: Efforts should be made to create algorithms and AI tools that are gender-neutral. Increasing diversity within data science teams and ensuring the production of diverse and representative datasets can contribute to achieving this goal.

Implement Gender-Inclusive Training Programs: Promoting gender-inclusive training programs will equip both men and women with the necessary skills to thrive in AI-related roles. These programs should be designed to bridge the existing skills gap and encourage equal participation in the AI workforce.

Ultimately, the impact of AI on gender equality will depend on today's initiatives to create gender-neutral AI systems. These efforts must prioritize inclusivity in AI design and development to ensure that algorithms and technologies do not perpetuate existing biases. By focusing on equitable practices, diverse data sets, and inclusive participation in AI research, we can shape a future where AI serves as a powerful tool for advancing gender equality rather than exacerbating disparities.

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