

WHEN AI MET GENDER: GENDERED IMPACT OF AI ON THE LABOUR MARKET

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Gendered impact of AI on the labour market

A report produced by the Global Institute for Women's Leadership, King's College London

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EXECUTIVE SUMMARY

The Core Argument

AI does not enter a vacuum: it enters a labour market that is already gendered, and without deliberate intervention it is likely to reproduce and deepen existing inequalities. Most debate on AI and work looks at variation by occupation, education or age and implicitly assumes gender neutrality. Where gender is addressed, it is largely through occupational exposure. This report brings gender to the centre, offering a theoretical framework of how AI interacts with gendered structures at the individual, organisational, occupational and labour market levels.

Theoretical Framework: four dimensions of gendered impact on the labour market

Two mechanisms run underneath. First, AI trained on existing data absorbs and can amplify gender bias, creating a self-reinforcing vicious cycle. Second, the gender division of unpaid care devalues "women's work" and leaves women less time to reskill, including learning to use AI itself.

Dimension	What happens with AI
Gendered access to and use of technology	Women use generative AI less partly from lower self-assessed competence and a greater sense of its risks: Domestic and care responsibilities also leave them less time to learn new skills relating to AI, leading to gender gap in career progression. However, even when they do use AI, they are penalised as they are deemed less competent. Furthermore, women only represent a fraction of the AI workforce. Decisions about which tasks are automated, and how, are being made largely without them.
Gendered organisation	Women face a double bind: falling behind without AI, penalised when they use it. Previous study finds that when shown identical AI-supported CVs, UK evaluators were twice as likely to question a woman's competence and more likely to doubt her trustworthiness, while a man's AI use read as initiative. Men are also more praised and more encouraged by managers to use AI. AI adoption gap therefore cannot be attributed entirely to the gap in confidence and certainly not to a gap in competence.



Occupational segregation and devaluation of "women's work"	Women make up a larger proportion of workers in the most AI-exposed in countries like the US, and accordingly ILO predictions, female-dominated jobs are twice as likely to be replaced. This reflects existing values within our societies which dictates which job is automatable and which job is worth automating. The devalued work already seen as "supporting" are often considered more completely replaceable. Much of women's work, especially unpaid care, attracts too little investment to be supported by AI at all. Furthermore, where it is automated, lack of data and misconceptions around the expertise of the already-devalued occupations tend to further devalue and deprofessionalise these jobs. Work for AI training could also contribute to devaluing the profession by reducing one's expertise to data, which could push down pay.
Overrepresentation in outsider jobs	Outsider jobs are more likely to be cut when exposed to AI than insider jobs, and women tend to be overrepresented in the outsider jobs, such as part-time, fixed-term, low-paid and gig work. AI could also further precarise the overall labour market as employers tend to reduce hiring, especially the standard employment, and a profession gets decoupled with tasks, providing ground for further expansion of gig economy.

AI's gendered consequences are likely to be sharpest where these dimensions intersect, not in occupational exposure alone.

Conclusion: a critical juncture

Technology is not deterministic. It reflects human decisions about what is worth building and whose work is worth preserving, taken overwhelmingly by men in high-income countries. However, what seems to be a bleak future for women is not inevitable. The report proposes questions to ask at this critical juncture at every stage of AI adoption. Broadly, they cover the following themes.

- **Development and investment:** Who receives AI funding, who is in the room, whose data and labour train the models, and what counts as success?
- **Use and implementation:** What barriers do women face in using AI, and what biases are amplified when AI is used in hiring or performance evaluation?

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- **Governance, accountability and voice:** Are employment, equality and data protection laws and unions equipped for AI harms, and are gendered effects being tracked?
 - **Outputs:** Who captures AI's gains and who bears its costs, and is automation of care and relational work depressing its pay and status?

The priority now is to question how AI interacts with existing inequalities, define an active role for the state in sharing both risks and benefits from AI, and proactively test and resist the biases embedded in and with AI.



INTRODUCTION

The last two decades have seen a continued interest in the impact of AI on the labour market with people like the CEO of Anthropic predicting that half of the white-collar jobs will be wiped out within the next five years¹. It is almost impossible to predict what future labour markets will look like, as technological developments are not only rapid, but many of the newest developments are also unknown to many. However, what is clear is that with the introduction of ChatGPT, Claude, and rapid development and awareness of AI technology, there are and will be fundamental changes in the way we work, the way labour markets are structured, as well as the inequality patterns that result from it. For example, we have seen a rise in youth unemployment rates in countries like the UK, with many noting the use of AI or the increase in AI investment in companies as some of the major causes of this drop in recruitment numbers². For instance, a Work Foundation survey of over a thousand UK employers in August 2026 found that 36% of firms had cut entry-level jobs, with the majority of larger companies citing AI and automation as the cause³. This has also led to increased fear of job loss among the population. For example, a recent study by the Policy Institute at King's College London found that 55% of university students believe AI will eliminate far more jobs than it creates, leading to widespread unemployment, while 60% believe that by the time they graduate, AI will have made the job market much tougher for them (Duffy et al., 2026). Indeed, 62% of them expect more than a quarter of entry-level roles to be replaced by AI within the next three years, and one in three (34%) believe AI will eliminate jobs so quickly that it will cause civil unrest.

Against this background, this report aims to critically review the current debates and literature around the impact of AI on the labour market and to introduce a theoretical framework of the gendered impact of AI bringing gender to the core of the debate. The majority of the extant literature focuses largely on the variation in the impact of AI across occupations or sectors (AI-exposed vs non-exposed), education levels (graduates vs non-graduates) or age groups (younger people or early-career entrants vs older workers). Much of the debate, for example, on AI and early-career employment, implicitly assumes gender neutrality. Where gender is addressed, it is largely through occupational exposure, for example, studies indicating that women's overrepresentation in clerical and administrative roles makes them more susceptible to automation (Gmyrek et al., 2025; ILO, 2026). Far less attention has been paid to the other channels through which AI may reproduce or even exacerbate gender inequality.

We argue that AI does not enter a vacuum but rather a labour market that is gendered. Indeed, we have seen a recent rise in papers exploring issues such as persistent gaps in adoption

¹ Chris Morris, "Anthropic CEO warns AI could eliminate half of all entry-level white-collar jobs," Fortune, 28 May 2025, <https://fortune.com/2025/05/28/anthropic-ceo-warning-ai-job-loss/>

² CIPD, "One in six employers say AI will shrink headcount as hiring confidence remains at record low," 10 November 2025, <https://www.cipd.org/en/about/press-releases/one-in-six-employers-say-ai-shrink-headcount-autumn-labour-market-outlook/>

³ Resultsense, "Six in ten large UK firms blame AI for fewer junior roles," 26 August 2026, <https://www.resultsense.com/news/2026-08-26-entry-level-jobs-work-foundation/>



(Cranney et al., 2026), with stronger calls to explore penalties for AI use⁴, bias in algorithmic hiring, the unequal time available for reskilling given care responsibilities, and the question of who captures AI-driven productivity gains. By identifying the gendered impact of AI across various dimensions of the labour market (i.e. at the individual level, organisational level, occupational level, labour market level), our framework demonstrates the complexity of the interplay among AI, the labour market and gender. The purpose of this report is in no way to provide a comprehensive scoping review of the growing literature on the impact of AI on the labour market and its gender implications. Rather, **our goal is to conceptually consider the potential dynamics of gender inequality that AI can bring about, based on our knowledge of the existing gender inequality structures currently in our labour market.** In this way, this report aims to serve as a starting point for a conversation on how we could ensure the AI-led economy can move towards mitigating the existing inequality in the labour market rather than exacerbating it.

This report comprises three sections. In the first section, we review the existing research on the impact of AI on the labour market with particular focus on displacement versus augmentation debate, by categorising them into three dimensions: 1) to what extent will AI impact jobs, 2) which jobs, and 3) for whom. Then, we further discuss the job displacement versus augmentation debate and introduce recent discussions that provide further nuance to move beyond such dichotomy. The second section brings gender into focus and introduces a theoretical framework to understand the complex relationship between gender, the labour market and AI. Finally, we conclude by proposing some key questions we must ask in the different processes of AI – e.g. starting from the investment into and design of AI systems, in its implementation, its governance structures, and in its outputs, to ensure that AI systems do not result in further increasing inequality patterns in the labour market. At the core of the argument lies the notion that rather than being deterministic, technological advancements are human-engineered and therefore need to be examined in terms of who makes those decisions, on whose behalf, and with what consequences for whom.

⁴ Code for Good Now (2026), *The AI Judgment Penalty*: <https://codeforgoodnow.com/wp-content/uploads/2026/06/Research-Report-The-AI-Judgment-Penalty.pdf>; Gai, P.J., Hou, J. and Tu, Y. (2025), “Competence Penalty Is a Barrier to the Adoption of New Technology,” SSRN Working Paper 5255039, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5255039 ; Acar, O.A., Gai, P.J., Tu, Y. and Hou, J. (2025), “Research: The Hidden Penalty of Using AI at Work,” *Harvard Business Review*, 1 August 2025, <https://hbr.org/2025/08/research-the-hidden-penalty-of-using-ai-at-work>.



IMPACT OF AI ON THE LABOUR MARKET

One of the key concerns when it comes to the impact of AI on the labour market or the future of work has been the possibility of job displacement by AI. The question is no longer whether AI can replace human labour, but rather which jobs, tasks or skill sets AI can replace and the extent of disruption it may have on the labour market. This strand of literature can be understood in three dimensions, which are: to what extent, which, and who.

1) TO WHAT EXTENT CAN AI REPLACE OUR JOBS?

Some studies have aimed to predict how much of the labour market can potentially be replaced by AI. Early studies investigated the extent of computerisation replacing the labour force, predicting 47% of the US labour force (Frey & Osborne, 2013) and 6-12% of the labour force across OECD countries (including the US) (Arntz et al., 2016) being at a high risk of automation. Recent studies after the introduction of ChatGPT further predicted that 1.8% of the US labour force is highly exposed to LLMs (Eloundou et al., 2024), and that **between 1% and 4% of occupations across countries are highly exposed to Generative AI** (Gmyrek et al., 2023). The most recent research conducted by OpenAI (Richmond, 2026) calculates that 18% of occupations in their consumer data are more likely to be automated by LLMs in the short term.

2) WHICH JOBS WILL BE REPLACED?

An important question when it comes to the job displacement by AI is *which jobs* will be most affected by this technological advancement. As we explore below, debate continues over **whether job displacement will be concentrated among lower-skilled, less educated workers or among the high-skilled, knowledge-based workforce, with evidence supporting both positions.**

Skill-biased technological change theory argues that the technology disproportionately advantages the skilled workers by augmenting their work while replacing the lower skilled jobs (Goldin & Katz, 2018). This has been used widely among economists to explain the increasing wage inequality driven by rising wages for the high-skilled workers. However, the seminal work by Autor et al. (2003) has shed light on the importance of the type of tasks conducted in a job, as the non-routine cognitive tasks are less likely to be affected by computerisation regardless of the skill-level required for a job. This approach has been used by Goos and Manning (2007) to explain the job demand polarisation observed in the UK, namely the continued demand for both the high-skilled and low-skilled workers engaging with non-routine tasks, in contrast to the decreasing demand for middle-skilled routine jobs. These studies, nevertheless, have also been contested as technology could further automate non-routine cognitive tasks (e.g., Brynjolfsson & McAfee, 2011; Frey & Osborne, 2013). Despite their contrasting views, both studies by Frey & Osborne (2013) and Arntz et al. (2016)



predicted that it is the low-skilled and lower educated workers who will be at the highest risk of automation.

However, recent developments in AI, especially since the introduction of ChatGPT, have shown a broader range of tasks being automated by AI, including in high-skilled jobs and, most notably, among knowledge workers (see also Agrawal et al., 2023). In terms of occupations, it is the computer programmers, customer service representatives, and financial analysts (Massenkoff & McCrory, 2026), as well as clerical workers (Gmyrek et al., 2023) that are expected to be most exposed to AI. While this exposure to AI has not (yet) manifested in the overall unemployment rate at an aggregate level, what is notable is the decrease in entry-level positions in the exposed occupations (Brynjolfsson et al., 2025; Klein Teeselink, 2025). Using the administrative dataset from Automatic Data Processing (ADP), Brynjolfsson et al. (2025) find a 6% decline in employment among young early-career workers aged 22 to 25 in exposed occupations between 2022 and 2025, despite the steady growth in overall employment within the same period. This contrasted sharply with the 6–9% growth in employment among the older workers. Among different explanations, one argument they make is that it could partially be due to generative AI replacing codified knowledge which comprises a large part of early career or recently graduated young workers' skills, while the tacit knowledge of the older or more experienced workers is difficult to automate. In the case of the UK, Klein Teeselink (2025) finds that the increase in AI exposure leads to a decline in employment especially for the junior positions as well as a decline in job postings. Namely, the first people to experience the impact of AI may be those who have not yet entered the labour market rather than those who are already in the labour market.

3) WHO IS AT RISK?

When it comes to the question of who is at risk, recent public debates have focused on education level, namely, whether or not the university graduates are shielded from this technological change, and some reports have pointed to the role of gender and women's higher risk of AI automation.

A notable observation from early studies on the impact of technology/computerisation was the increasing demand for higher education even for the low-skilled workers (Autor et al., 2003; Goos & Manning, 2007). In contrast, what the recent predictions after the development of large language model AI demonstrate is that it is the higher-educated workers who are more concentrated in highly AI-exposed occupations than lower-educated workers (Massenkoff & McCrory, 2026; Muro et al., 2019). What this means is not that the university degree itself is susceptible to AI exposure, but that the occupations that require university degrees tend to be highly exposed to AI. This, combined with fewer entry-level jobs, indicates that the **university-graduate labour market entrants may be among those whose labour market security is impacted the most by AI**. In the UK, applications to AI-exposed degrees have grown even as junior positions in the corresponding occupations have declined (Vossos et al., 2026), and hiring has fallen most in AI-exposed firms and occupations, concentrated in junior roles (Klein Teeselink, 2025). As mentioned in the previous section, there are differences not only in the age group of workers who are affected – namely young and early-career entrants – but also in the field of work (Brynjolfsson et al., 2026). Thus, the mismatch between the share of labour market entrants and the entry-level positions in the AI-exposed jobs is predicted to increase in the near future.



Another group that has been identified as being at a high risk of **job displacement due to AI is women and those working in female-dominated sectors** (Fernandez et al., 2026; Gmyrek et al., 2023; LinkedIn, 2023; Massenkoff & McCrory, 2026). Based on Anthropic's prediction using US Current Population Survey, 54.4% of workers in the highly exposed occupations are women, which contrasts with 38.8% among those with no AI exposure (Massenkoff & McCrory, 2026). Across the world, it has been reported that female-dominated jobs are twice as likely to be replaced by AI as male-dominated jobs (ILO, 2026). 3.7% of working women worldwide work in occupations that are highly likely to be automated, in contrast to 1.4% of working men, meaning that women are almost three times as exposed to automation risks (Gmyrek et al., 2023). The same study finds that in high-income countries, these numbers reach 7.8% for women and 2.9% for men. Generally, the shares of women in jobs that are likely to be automated and in jobs that are likely to be augmented were both high globally, which indicates that the impact of AI is likely to be large for women. **Even within STEM occupations, women are more likely to be in the entry-level positions than higher level positions and to be overrepresented in jobs that are being replaced more** (e.g., creative jobs such as graphic design) (Lieser et al., 2026). Gmyrek et al. (2023) also find that in upper-high-income and high-income countries, the share of women in total employment working in occupations with unknown effect of AI (the 'big unknown' neither clearly automation nor augmentation-prone) is also larger than that of men. Conversely, Muro et al. (2019) show that more highly AI-exposed occupations are often more male-dominated; and in lower income countries, a greater share of men are working in occupations under the 'big unknown' category (Gmyrek et al., 2023). Fernandez et al. (2026) find greater exposure to LLMs for female-dominated occupations, whereas male-dominated occupations show greater exposure to broader AI innovations that are more high-impact. Furthermore, while Klein Teeselink (2025) finds that it is the higher wage occupations that are at a higher risk of AI exposure, Fernandez et al. (2026) find that this only applies to male-dominated occupations, as for female-dominated occupations the risk is distributed across (high-skilled) high-paid occupations and (low-skilled) low-paid occupations. Overall, these findings demonstrate **complex gender dynamics that are at play in the impact of AI, which require a closer investigation**. We will discuss this further in section two of this report.

4) BEYOND THE DICHOTOMY OF DISPLACEMENT VERSUS AUGMENTATION

Being exposed to AI does not necessarily mean that a job will be automated or that it will have a negative impact on the labour market. AI tools often automate certain tasks within a job rather than an entire job (as discussed in Arntz et al., 2016; Eloundou et al., 2024), and it may in turn help facilitate the non-AI-exposed tasks and increase productivity (Noy & Zhang, 2023). Current models of AI also have limitations that require human labour, such as training AI, managing data and assessing the quality of outputs (Zysman & Nitzberg, 2024). Agrawal et al. (2023) further argue that AI may even make certain high-skill tasks accessible to the lower skilled workers and may contribute to reducing labour market inequality.

While the impact of AI on the labour market is often deemed ambivalent with contrasting views on whether AI will displace or augment jobs, recent studies focus on its potential for both (Chen et al., 2024) and how it may unfold differently depending on the occupations or other factors that influence the impact of AI (Gmyrek et al., 2023; Richmond, 2026). In



particular, Richmond (2026) has argued that when it comes to the actual impact of AI on the jobs that are highly exposed to it, we also need to take into account the necessity of humans in that job and the potential increase in labour demand with increased productivity by using AI. Depending on these factors, a job may be automated, or experience changes in its tasks, or even see a growth in demand. **The human necessity in a job refers to both the importance of humans being involved in the job rather than relying entirely on AI, and the societal value of whether a job needs to be done by a human or not.** For instance, an example provided by Richmond (2026) is a judge, whose tasks can technically be replaced by AI, but as a society we would prefer humans to be undertaking such a role. Thus, changes in the labour market brought about by AI are driven not only by technology itself but also by the values and morals of society (Wajcman, 1991a, 1991b, 2004). Drawing on previous waves of technological advancement, Autor (2024, p. 14) predicted that AI would bring “new goods and services, generate new demands for expertise and open new possibilities for human advancement” that we cannot yet know, which in turn can create new opportunities for certain expertise. Thus, while some jobs will get automated, some new jobs may be created. However, such gain and loss logic only works at an aggregate level, as for individual workers, the new jobs created may not necessarily be available to those who are at risk of losing their jobs. **There is often a mismatch between the skills of those who have lost their jobs to AI, and the skills that are needed for the new jobs created post AI adoption.**

Against this background, we point to two major limitations of the displacement versus augmentation debate: first, it mainly focuses on what an AI can do *theoretically*, and second, it hides individual workers’ experience and its variation behind aggregate statistics.

First, **who is exposed to AI and the extent to which they are exposed remain largely theoretical.** It is limited to predicting what the AI can potentially do when in reality both replacement and augmentation depend heavily on the institutional, sectoral and organisational contexts (De Stefano & Doellgast, 2023; Doellgast et al., 2025; Lloyd & Payne, 2019; Milanez, 2023; Zysman & Nitzberg, 2024), such as industrial relations, labour market protection policies, AI regulations, organisational priorities as well as managerial decisions. Namely, **the missing piece of the puzzle is the context into which AI enters, and the human agency in shaping how an AI is adopted and used.** These contexts could shape who adopts AI and how an AI is adopted at a workplace. For instance, when AI is introduced in the workplace, strong works councils supported by institutional power from laws and collective bargaining could ensure AI regulations are in place to protect workers’ rights (Doellgast et al., 2026). Furthermore, the impact of AI goes beyond what an AI can do. Mass layoffs that we have witnessed in large tech companies in recent months are not necessarily due to AI replacing workers but instead employers’ investment decisions that put more emphasis on AI development over training workers. For example, a survey of over 1,000 executives found that AI-attributed layoffs were almost entirely made in anticipation of AI’s impact rather than in response to demonstrated productivity gains (Davenport & Srinivasan, 2026). Similarly, we have seen how some of the largest tech firms have executed layoffs while simultaneously raising AI capital expenditure to unprecedented levels⁵, effectively redirecting payroll towards

⁵ For example, Meta announced that it would cut around 8,000 jobs in April 2026, roughly 10% of its workforce, and close a further 6,000 open roles. Its internal memo stated that the cuts were intended to “run the company more efficiently and to allow us to offset the other investments we’re making” (Bloomberg (2026) Report on Meta internal memo announcing workforce reductions, 23 April.). Days later, the company reported first-quarter revenue of \$56.3 billion, up 33% year on year, and raised its 2026 capital expenditure guidance to



AI infrastructure (Spangler, 2026; see also, BSI, 2025). This demonstrates that the impact of AI goes beyond an occupation's exposure to AI, as employers' decisions on (or potential restrictions on) investing in AI systems versus their workforce are another important dimension to consider.

Second, as mentioned above, whether AI will replace or augment a job is often discussed at an aggregate level, assuming that there is a single market whereby all workers within an occupation are equally affected by AI. However, the labour market in reality is segmented and unequal. Namely, some are more vulnerable to the negative impact of AI than others and some are more likely to be shielded from changes brought by the new technology than others. As mentioned above, evidence shows that the young labour market entrants are largely affected by AI (Brynjolfsson et al., 2025; Gmyrek et al., 2023), potentially driven by the reduced entry-level positions and companies' increased investment in AI rather than using that investment to hire and train new workers. What we do not yet know is, when an occupation is exposed to AI, who among its workers gets replaced first and who would get the opportunity to upskill and use AI to augment their jobs. For instance, it may be those already holding fixed-term employment contracts who are at a higher risk of redundancies than those with open-ended or permanent contracts, or younger workers versus older workers, as we have seen in previous economic shocks (Chung et al., 2012; Emmenegger et al., 2012). It may also be those who are already considered secondary earners of a family or those who are considered low-skilled who are at a higher risk of being let go or replaced based on employers' bias and assumptions (Benard & Correll, 2010; Njoto et al., 2025). Such inequality can be further heightened when AI is used for hiring or management processes, as it can create a systematic bias that disadvantages marginalised groups in the society (Bommasani et al., 2026). While further investigation is required, we argue that this is closely related to the existing labour market inequalities as well as the norms and assumptions of who the 'core' and 'ideal' workers are (Acker, 1990; Emmenegger et al., 2012). Therefore, the impact of AI on the labour market needs to be understood from the labour market perspective, namely how AI enters an existing labour market and its existing structures, biases and inequalities.

Furthermore, what requires greater attention is what happens to a job, work organisation and a profession when AI is introduced. Increased work intensity and work pressure can be outcomes of increased efficiency (Christenko, 2024; Mateescu et al., 2026). When jobs are partially automated, it could also undermine job quality, not only in terms of wages and job security but also the professionalism or integrity of the job (Autor & Thompson, 2025; Gmyrek et al., 2023; O'Connor, 2026; Ranganathan & Ye, 2026). Mateescu et al. (2026) find that when one's work is used as data for an AI system, the work itself may lose its meaning and be reduced to data. As a result of this, along with the heightened uncertainties around the impact of AI, workers' individual bargaining power may be reduced, and the fear of losing one's job may lead to greater pressure from work. Moreover, work organisation itself may also change with AI. Aside from algorithmic management, the introduction of AI into a workplace as a co-worker allows for a more horizontal work organisation, blurring boundaries between roles (Luengo Vera et al., 2026; Mayer et al., 2025).

\$125–145 billion, largely for AI infrastructure (Meta Platforms, Inc. (2026) *Meta Reports First Quarter 2026 Results*. Press release, 29 April. Available at: <https://investor.atmeta.com/investor-news/press-release-details/2026/Meta-Reports-First-Quarter-2026-Results/default.aspx>).



GENDERED IMPACT OF AI ON THE LABOUR MARKET

This section draws on the existing literature on gendered labour market inequalities, to explore what the current and potential impact of AI can be on the gender inequality patterns in the future. Gendered impact of AI here refers to how AI interacts with the labour market that is already gendered and its gendered consequences. We focus specifically on four interrelated dimensions of gendered patterns in the labour market, which shape how AI is used and adopted differently across gender lines, potentially further enhancing the gender inequality in the labour market. We aim to propose a theoretical framework (see Figure 1) that allows for a nuanced understanding of the interplay between gender, AI and work, beyond gender bias of AI and greater AI exposure among female-dominated than male-dominated occupations. Before discussing individual dimensions, we first address two key underlying mechanisms that are crucial in understanding the gendered impact of AI.

First, AI systems, and large language models in particular, are trained on vast quantities of existing text, largely scraped from the internet⁶, and therefore absorb the social norms, hierarchies and stereotypes embedded in that data. **The use of AI can therefore reinforce gender bias in society, when humans do not reflect on and correct for the existing biases in the data used.** For instance, comparative studies of large language models found that large language models show biased assumptions about whether an occupation is for women or men (Kotek et al., 2023) and suggested a lower salary for women than men (Sorokovikova et al., 2025). A recent study further found that even when existing biases are adjusted, large language models tend to develop new biases based on their own learned data (Wu et al., 2025). When such tools are used for job advice or hiring and promotion processes, gender bias that already exists in the society could be further reinforced. What is important is that the reinforced gender bias could feed back into the AI model, creating a vicious cycle of gender bias reinforcement. For our theoretical framework, we note that each dimension of gendered labour market patterns could form such a vicious cycle with AI.

Second, a key mechanism that underlies all dimensions discussed below is the gender division of labour and underlying gender norms. The current gender division of labour rests on assumptions about the efficiency of household specialisation (Becker, 1981) and on gendered beliefs about men's and women's respective roles and strengths (Ridgeway, 2011). This division is especially problematic because **'women's work', that is, work associated with the reproductive sphere such as care and domestic labour, is systematically undervalued in market terms** (England, 2005; Folbre, 2001). This is not only because such work has historically been performed by women unpaid within the household (Federici, 1975; Oakley,

⁶ Initial LLMs were largely based on web crawls (e.g. Common Crawl, the most commonly used, a public archive of billions of web pages), books, code, academic and scientific texts, forums and social media, and even synthetic data. There were some concerns raised in the earlier stage of LLMs where the data used to train the machines were based on potentially problematic web forums, and even now there are some concerns that given the enhanced security many publishers or websites put up to stop web crawls, LLM training is not based on “neutral” data.

1974), but also because of historical gender power structures that devalue work once it becomes associated with women (Acker, 1990; Fraser, 2016; Levanon et al., 2009). This, along with the assumption of women being the second earner, further places women at the periphery of the labour market with jobs that are inherently precarious, such as part-time or insecure jobs, which women are already more likely to hold compared to men (Chung, 2024; Seo, 2021). The gender division of labour is further manifested through persistent bias regarding women in STEM. The under-representation of women in STEM jobs, particularly in senior management, sustains societal assumptions that women are less capable in these areas. These assumptions shape both how others evaluate women and how women assess themselves.

Furthermore, the actual disproportionate amount of unpaid work within a household whereby women, mothers in particular, take up the bulk of care and household work can limit women's ability to reskill to catch up with the rapidly changing labour market, given that they have less protected time to be able to do so. Time constraints due to work or family responsibilities are the most commonly cited barrier to adult learning, and women are significantly more likely than men to report facing such barriers (OECD, 2025). The same constraint applies to learning to use AI itself: care responsibilities leave women less discretionary time to invest in learning new tools whose payoffs are uncertain (Cranney et al., 2026). Given the increasing number of jobs requiring AI skills, and AI skills commanding higher wages than other skills (PwC, 2026), difficulty reskilling could further lead to disadvantages from hiring through to promotion, widening the gender pay gap.

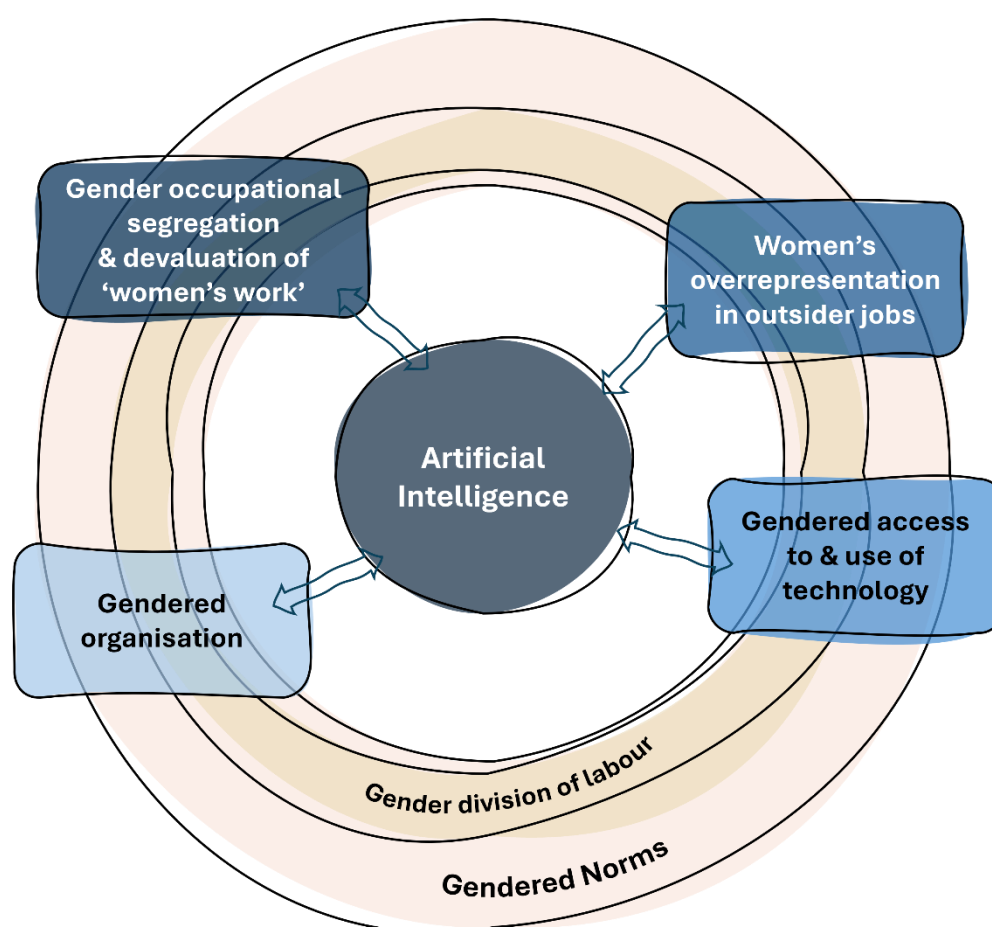


Figure 1 Theoretical framework of gendered impact of AI in the labour market



1) GENDERED ACCESS TO AND USE OF TECHNOLOGY

Under current cultural norms, science and technology are culturally coded as masculine, due to existing power dynamics in society (Wajcman, 2004). Women are socialised to have less affinity with technology and social norms pressure them to believe that they are less competent in math and science than men from an early age (Correll, 2001). Despite no significant biological or innate differences between the male and female brain (Fine, 2011), or in the brain processes underlying maths and science ability between girls and boys (Kersey et al., 2019), women are and have been underrepresented in STEM (Science, Technology, Engineering and Mathematics). According to the latest workforce data from Women into Science and Engineering (WISE) (2025), women make up 27.2% of overall Core STEM roles and 18.2% of science, engineering and technology (SET) managers in the UK without large changes in the last decade. Even among those who are working in the technology sector, women are more likely to be laid off and leave their jobs than men (WomenTech Network, 2026). A 2022 study by Gotara (2022) has shown that roughly 40% of women in STEM leave their jobs within 5-7 years, which is significantly higher than the 23% for men. The 2025 Lovelace Report further found through its survey on women in tech across the UK that almost 80% of them either have recently left or would like to leave their current jobs due primarily to limited opportunities and managerial support (O'Neill et al., 2025).

What is more, there is evidence to show how **gender bias in hiring and promotion is strong in STEM**, perhaps stronger in comparison to other areas of society, even when candidates' performance is identical (Moss-Racusin et al., 2012; Reuben et al., 2014). The bias is so prevalent that even women themselves rate their own mathematical competence lower than men with identical performance, which steers them away from STEM careers (Correll, 2001, 2004).

This has two important implications for the gendered impact of AI. First, **women may feel less competent to use AI (as a new technology) for their jobs than men, leading to an AI adoption gap** (Aldasoro et al., 2024; Hupfer et al., 2024; WomenTech Network, 2026). Survey data from the US show that women tend to use generative AI tools less than men, largely due to lower self-assessed knowledge of generative AI (Aldasoro et al., 2024). Although a more recent study in the UK finds that this gender AI adoption gap cannot be entirely attributed to perceived competence but also reflects perceived societal risks and consequences of AI (Stephany & Duszynski, 2026), what we consistently observe is that the gap exists (Cranney et al., 2026). This gap in AI adoption could lead to gender gap in career progression as well as the gap in reskilling to meet the new demands of the AI-led economy as discussed above. What is more, even when women do use AI, they are judged as less competent than men producing identical work (Chatoo, 2026; Gai et al., 2025). The same stereotype that questions women's technical ability thus penalises women twice: for lacking AI skills, and for using them.

Second, **women make up only around a fifth of the AI workforce** (Young et al., 2021), so **the technology is largely designed without them**. A similar gender gap is evident when we look at the authors and inventors of AI publications and patents across the globe, with more than 80% of AI talent being men in some countries (e.g., Brazil, South Korea, and Japan) (Sajadieh et al., 2026). This is potentially due to the existing biases discussed above in addition to the problematic work cultures in many of the AI and other tech companies which are characterised as 'masculine contest cultures' (Berdahl et al., 2018). Considering that the tech companies are leading the AI development globally, fewer women in tech jobs means



that fewer women are involved in designing and developing the AI. As mentioned above, female-dominated occupations are predicted to have higher risk of replacement by AI than male-dominated occupations (Gmyrek et al., 2023; ILO 2026; LinkedIn, 2023). From this we can infer that not only are women having to rely on an AI system designed predominantly by men, but they are also likely to be the ones to experience disruption in their jobs by AI, which partly could also be due to the decisions made in the design and application of AI into our labour market systems in which women do not have much of a say. This could also influence the future direction of work models where gender bias continues to be embedded in them. **Which tasks are replaceable and how we work with AI is primarily shaped by which AI is developed and how. Thus, limited voice of women and other minorities in AI design could further shape new gendered patterns in the labour market.**

2) GENDERED ORGANISATION

Previous scholars have identified that rather than being neutral, organisations are gendered in the way they are structured and operate, with advantage and disadvantage, meaning and identity, and patterns of control patterned through distinctions between male and female (Acker, 1990). Central to this is the notion of the ‘ideal worker’ in an organisation, who often works long hours and can devote themselves to work without any obligations outside of work (Williams, 1999). This model of organisation and worker is inherently designed to advantage ‘masculine’ traits and heterosexual white men, and this model is especially dominant in male-dominated occupations and sectors (Berdahl et al., 2018). Under this cultural norm, women and feminine qualities are less valued, women, especially mothers, are viewed as less competent and their work is more contested compared to men (Ridgeway & Correll, 2004). Gender operates as a status characteristic, generating expectations that men are more generally competent than women, so that identical performance is read differently depending on who produced it (Ridgeway, 2011). Women, as well as ethnic minorities, are consequently held to stricter standards: evaluators apply double standards for competence, requiring more evidence of ability from women before conceding it, and less evidence to confirm a lack of it (Biernat & Kobrynowicz, 1997; Foschi, 2000). Where women's achievements are unambiguous, their competence may be conceded but their success attributed to luck or effort rather than skill or accompanied by penalties for violating expectations of femininity (Heilman & Haynes, 2005; Rudman & Glick, 2001). Women must repeatedly prove competence that men are presumed to have, and their claims to expertise remain open to challenge in a way men are not.

Using AI is not free from this gender bias within the organisation. An experimental study reveals that when AI is used, female engineers’ competence is questioned more than that of male engineers (Gai et al., 2025). A similar split-sample experiment on 1,000 UK adults found that evaluators were twice as likely to question the female candidate's competence and 22% more likely to doubt her trustworthiness, compared to the hypothetical male candidate whose AI use was perceived as evidence of initiative and pragmatic problem-solving, when shown identical AI-supported CVs that differed only in gender (Chatoo, 2026). A survey conducted in the US by Lean In (Noble-Tolla 2026) also found that men tend to be more praised for using AI and are more encouraged by their managers to use AI than women. Women, meanwhile, are more worried than men about negative perceptions of their AI use. The evidence indicates that **AI could become another source of a double bind for women, where**



they may not be able to compete with their male peers without using AI but also could face stronger penalties when they do use it.

It is therefore not a coincidence that women tend to have a more cautious approach towards AI adoption than men. A recent survey by the Policy Institute and the King's Institute for Artificial Intelligence shows how women are substantially more negative than men about AI's likely consequences. 44% of women disagree that AI is positive for humanity, against only 18% who agree, whereas 35% of men disagree and 30% agree. Similarly, only 22% of women agree that AI will improve their lives compared to 41% that disagree, while more men (30%) agree to this statement (Duffy et al., 2026). Likewise, a Canadian survey of 3000 respondents has found that women perceived AI as riskier than men did, and women's support for companies taking up AI declines faster when its net positive effect on employment declines (Borwein et al., 2026).

The double bind of AI use is only one of many ways in which the gendered organisational context will shape not only the AI adoption gap, but also how AI comes to exacerbate existing inequalities in labour market evaluation as its use becomes normalised. **The AI adoption gap therefore cannot be attributed entirely to the gap in confidence and certainly not to a gap in competence. It is important to understand how the underlying gender structure within an organisation could impact the way in which AI adoption shapes gendered outcomes in employment and career progression.**

3) GENDERED OCCUPATIONAL SEGREGATION AND DEVALUATION OF 'WOMEN'S WORK'

Occupations are segregated by gender, and there are jobs that are dominated by women and those that are dominated by men (Charles & Grusky, 2004; Reskin, 1993). The occupations women are more likely to be in and are associated with femininity tend to be considered low-skilled and are often devalued and paid less than the male-dominated occupations (Levanon et al., 2009; Reskin, 1988).

It is not only female-dominated occupations that are highly exposed to AI (Muro et al., 2019). Some male-dominated occupations, such as computer programming, are also highly exposed to AI, – and some female-dominated occupations, such as care work, seem to be shielded from AI. However, evidence consistently shows that on average, **more female-dominated occupations are at a higher risk of AI exposure than the male-dominated occupations** (Gmyrek et al., 2023; ILO, 2026; LinkedIn, 2023; Risse & Stephenson, 2026). A recent report by Fernandez et al. (2026) further finds that the exposure to large language models is particularly high for female-dominated occupations, and unlike male-dominated occupations, even the low-skilled occupations (along with high-skilled occupations) are at a high risk of AI exposure. Some of the typical occupations include clerical and administrative workers. While these studies reveal important, gendered patterns in the impact of AI, many of these predictions often assume gender neutrality of technology, namely, that it is purely based on the tasks an AI can do. However, we argue that the **diverging patterns for female- and male-dominated occupations need to be understood within the context of devaluation of 'women's work'** (Reskin, 1988). In the case of automation, women's work may be considered work that can be fully automatable, which does not necessarily need human expertise.



As discussed above, both AI systems and the roles that they are expected to play reflect society's values, including key decisions such as which jobs are considered of value and irreplaceable. Whether a job will be replaced or augmented by AI **does not solely depend on the ability of an AI or robots to carry out the task proficiently, but also on social judgements on whether humans are needed to conduct the work or not** (Richmond, 2026). Thus, how AI is adopted in practice cannot be separated from what society values or devalues, and gender relations may be reinforced rather than reimagined. This operates in two directions.

On the one hand, a job that is already devalued and considered a 'supporting role' is more readily viewed as something to be entirely replaced or automated. As mentioned above, while overall high-skilled workers show high exposure to AI, for female-dominated occupations, it is also the low-skilled or low-paid jobs that are at a high risk of AI exposure (Fernandez et al., 2026). Some of the most AI-exposed occupations, such as customer service workers, clerical workers, and other back-office workers often have skills that are not easily transferable to new jobs that may be created through AI and may need time and resources to adapt⁷. This is therefore the very group of people for whom the aggregated logic of job lost and created offers the least assurance, since they are least likely to be able to readily move into the potential new jobs created by AI.

On the other hand, some tasks may be so devalued that they are not deemed worth automating due to lack of profitability. An example of this could be unpaid work including mental load⁸. Although many women would welcome technologies that free up their time and mental space, such tools attract little investment because some investors may see limited commercial return. In fact, some technologies have been developed in the past to support domestic work, but they did not reduce women's domestic labour as promised, because standards rose and the gendered division of labour held (Bittman et al., 2004). In the robotics and AI era, domestic and care work has attracted a fraction of the investment directed at industrial automation, logistics and transport, despite the time it consumes. Rather than a matter of technical difficulty, it is due to expected returns, as work performed unpaid within the household generates no market signal to direct it, and the ready availability of women's unpaid or cheaply purchased labour (e.g. that of women and migrant workers) further weakens the incentive to automate (Folbre, 2001).

What is crucial here is that *which* AI is developed and *how* it is designed is not a product of neutral technological developments or what is valued by society but instead determined by what is valued by the investors and large technology firms, who are predominantly men (Wajcman et al., 2023, 2024). Therefore, AI's higher likelihood of replacing female-dominated occupations rather than augmenting them when compared to the male-dominated occupations, may not merely reflect the more repetitive or more automatable nature of the

⁷ Ben Casselman, "The Hidden Workers Most Threatened by A.I.," The New York Times, 10 June 2026, https://www.nytimes.com/2026/06/10/business/economy/back-office-workers-ai.html?unlocked_article_code=1

⁸ However, it has been reported that data collection work of domestic labour in order to build an embodied AI has been taking place in some countries, notably India. How this will unfold and its impact on gender division of labour globally remains to be seen but requires close investigation.



tasks themselves, but rather the long-standing devaluation of what we consider a ‘women’s work’

Devaluation of female-dominated occupations could also be further reinforced with the expansion of AI in our labour markets. When an occupation is devalued, the skills and expertise it requires can be poorly understood leading to misconceptions around what can be automated (Kawakami et al., 2024). For instance, it is often difficult to define what expertise and skills are required for care work and what tasks can be automated in ways that support care workers without eroding their professionalism or the human elements at the heart of the work. This lack of knowledge (or data) could lead to “AI Failure Loops” (Kawakami et al., 2024) whereby AI adoption could further enhance the devaluation or professionalisation of the occupation, reducing workers to mere cogs in a larger machine (O’Connor, 2026). **Choices about which skills are viewed as essential human skills that must be retained and what can be automated, as well as the role humans have alongside an automated system, are not merely technical questions but also political ones.**

Furthermore, automating a task requires data on how the task is done, and it is often collected through workers’ own labour, whether it be in a text format or a video format. Yet, the work that is required to build an AI system is often recast as data rather than labour, leading to what Mateescu et al. (2026) refer to as ‘erosion of occupation’. In other words, the **automation process in itself may result in the devaluation and the deprofessionalisation of occupations. The resulting systems then could further lower the value of an occupation, which often manifests through lower wage.** Translation provides a clear example of this. With the rise of widely available translation tools, translation has been one of the hardest-hit occupations. Already in 2024, a survey by the Society of Authors showed that roughly 40% of translators had experienced a decrease in their income due to generative AI. This decline arguably reflects not only the technology’s capabilities, but also a wider tendency to regard translation as a mechanical task rather than a skilled, interpretive craft. Similarly, the work of many creative workers (e.g., graphic designers, writers) has been quietly converted into training data for AI often without *consent, compensation or credit*, namely “the 3 Cs” (Jiang et al., 2023; Kyi et al., 2025). According to a survey conducted in 2023 with leaders and managers of creative businesses in the entertainment industry, 75% of them indicated that generative AI has led to job losses or consolidations (CVL Economics, 2024). Often hired in the form of gig work, they are particularly vulnerable to losing work to AI trained on their output and to falling pay (The Society of Authors, 2024)^{9,10,11}. **Again, when women are absent from the decisions about what is automated, which parts of jobs are automated, what role (if any) humans will play,**

⁹ Translators refer to this as “digging your own professional grave”. Lianne Kolirin, “Like Digging ‘Your Own Professional Grave’: The Translators Grappling with Losing Work to AI,” *CNN*, 23 January 2026, <https://edition.cnn.com/2026/01/23/tech/translation-language-jobs-ai-automation-intl>

¹⁰ Duolingo has cut jobs for contractors after developing AI content. Lauren Forristal, “Duolingo Cuts 10% of Its Contractor Workforce as the Company Embraces AI,” *TechCrunch*, 9 January 2024, <https://techcrunch.com/2024/01/09/duolingo-cut-10-of-its-contractor-workforce-as-the-company-embraces-ai/>

¹¹ See testimonies of visual artists, illustrators and graphic designers. Brian Merchant, “Artists Are Losing Work, Wages, and Hope as Bosses and Clients Embrace AI,” *Blood in the Machine*, 16 September 2025, <https://www.bloodinthemachine.com/p/artists-are-losing-work-wages-and>



and whose jobs will be further devalued, more of women's work may end up devalued, underpaid and/or diminished.

4) WOMEN'S OVERREPRESENTATION IN OUTSIDER JOBS

The labour market is segmented, and women are overrepresented in outsider jobs (Schwander & Häusermann, 2013; Seo, 2021, 2023). In the dualization literature, outsiders are often defined as those who are at the periphery of the labour market outside of the labour and social protection, as opposed to some workers such as those with standard employment relationships who usually have such protection (i.e. insiders). While the definition of an outsider remains ambiguous, outsiders often represent those in non-standard employment, low income, and/or without social protection such as social insurance coverage. Women are overrepresented in nonstandard employment, especially part-time work (Chou et al., 2017), and low-income jobs across advanced economies (Beghini et al., 2019). Considering the different configuration of outsider jobs, Seo (2021) found that women are especially overrepresented in jobs that are low income and without prospects for advancement across Europe. Gig work (i.e., on-demand, task-based jobs often contracted through online platforms) is a type of outsider job, which has sometimes been considered an opportunity for women to enter the labour market with its high level of flexibility, but in turn has enhanced the precarity of many female workers due to the precarious nature of the jobs (Gerber, 2022).

Understanding labour market segmentation between insiders and outsiders has an important implication for the impact of AI exposure to a job, as the outsider jobs, especially those with fixed-term (employment) contracts, are deemed inherently more easily replaceable as they do not constitute the 'core skillsets' of an organisation. Even when the same occupation is exposed to AI, outsiders are more likely to be replaced or let go when there is a need for cost cutting. This could also be the case for the non-AI-exposed occupations, when employers are faced with the need for cost cutting under the uncertainties of the labour market or enhanced competition due to the advance of AI or their goals to focus on the return on investment in AI. **Given women's overrepresentation in outsider jobs, women are inherently at a higher risk of losing their jobs with the advancements of AI.**

Furthermore, AI could further make the entire labour market more precarious and worsen the working conditions of all workers. On the one hand, under the uncertainties of AI technology, return on its investment and how it may change the organisation, employers may not only opt for hiring fewer workers but also opt for hiring fewer workers on standard or permanent contracts that provide workers with job security and protection. On the other hand, deprofessionalisation which decouples a task and a profession could further accelerate the advancement of the gig economy as more jobs are reduced to individual tasks. Contracts in the gig economy often lie outside of existing legal protection for workers due to their ambiguity in employment status. While the EU Platform Work Directive introduces a legal presumption of employment, uncertainties remain due to limited control around their work, no precedents of long-term career-building and still-limited social protection (De Becker et al., 2024), individualising the social risks (Vallas & Schor, 2020). This type of contract has already begun to flourish in digital platforms (e.g., De Stefano, 2016; Wood et al., 2019), but in recent years has been accelerated by AI, reaching various occupations, even those that were traditionally



characterised by secure jobs, such as nursing¹². Work needed to train or manage AI especially has been susceptible to gigification, with some AI companies even hiring professionals such as doctors, lawyers and bankers to train AI models¹³.

While these changes would increase the overall precarisation of the labour market, the structural mechanisms that disadvantage women and limit them to outsider jobs (Seo & Kim, 2026) are likely to persist. What emerges, then, is a compounding of disadvantage. **Women are more likely to hold outsider positions within occupations, where precarious contracts limit their bargaining power, and to be concentrated in outsider sectors, where collective representation and regulatory protection are weakest. It is at this intersection, rather than in occupational exposure alone, that AI's gendered consequences are likely to be sharpest.**

¹² Arielle Pardes, “Gig Workers Are Endlessly Exploited. AI Could Make More of Us Share Their Fate,” *The Guardian*, 18 June 2026, <https://www.theguardian.com/technology/2026/jun/18/ai-threatens-gig-work-rise>

¹³ Arielle Pardes, “Gig Workers Are Endlessly Exploited. AI Could Make More of Us Share Their Fate,” *The Guardian*, 18 June 2026, <https://www.theguardian.com/technology/2026/jun/18/ai-threatens-gig-work-rise>



CONCLUSION

Much of the existing literature on the impact of AI on the labour market often adopts a technologically deterministic view of the changes now under way. It assumes that outcomes follow from technological capabilities, and that decisions about what gets built or developed, and therefore what gets automated and how it is implemented, are neutral, bias-free and essentially apolitical. **Yet technology is not an autonomous force acting upon society from outside. It is the accumulated product of human decisions about what is worth developing, whose problems merit solving and whose work is worth preserving, taken overwhelmingly by men in high income countries, and a very specific group of men at that, inevitably carrying with them the values and assumptions of those who make them** (see also, Wajcman, 2004). Therefore, we need to acknowledge that AI can be introduced into a labour market biased against certain workers and in which some workers are already at a higher risk of losing their jobs or working with limited prospects for advancement. While critically reviewing the existing literature, this report aimed to bring gender to the core of the discussion and demonstrate the ways in which AI could impact women and men differently, considering the different dimensions of existing gendered labour market patterns, and how these existing inequality patterns can, or have already, translated into AI-induced labour market inequalities.

Although the gender bias and inequality patterns that permeate both our labour market and the AI systems now being built into it seem to point to a bleak future of work for women, this future is not inevitable. **We are at a critical juncture, at which the direction in which we are heading can shift to ensure a more gender egalitarian and inclusive labour market.** We cannot promise a comprehensive solution to a question this complex and fast-moving. AI is developing at extraordinary speed, and its implications for the labour market and for society as a whole remain uncertain, even too many of those building the systems themselves. What we can do, however, is set out a number of questions that need to be asked if the development and application of AI is not to replicate or exacerbate existing patterns of inequality. These questions are not exhaustive, but they reflect the issues raised in this report concerning gender inequality and the barriers women face in taking part in the discussions and decisions that shape these technologies. Gender is the lens we adopt here, though the same questions apply to race, disability, sexual orientation, class and other dimensions of inequality. Below we propose some questions we can begin with.

AI Development and investment

- Who is receiving money and investment, by both investors and government, to develop AI systems¹⁴? Are they representing the wider society? Are they investing (in products and systems) with societal interest at heart or for the powerful few?

¹⁴ See also Wajcman, J., Young, E., and De Miguel Velazquez, J. (2023). *Rebalancing Innovation: Women, AI and Venture Capital in the UK*. The Alan Turing Institute. And Wajcman, J., Young, E., and Kampmann, D. (2024). *Rebalancing Innovation: Women, AI and Venture Capital in the UK Second Report*. The Alan Turing Institute.

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- Who is in the room when decisions are made around what is being developed/automated, and how/why? Is it bringing diverse voices and concerns into the decisions?
 - Why and how are work cultures and gender discrimination pushing women out of AI and, more broadly, out of STEM, especially in decision-making roles? What changes do we need to ensure this barrier is removed?
 - What data is being used to train the models? Do they have any gender bias embedded in them? Whose labour is used to produce data, how is the data collection and processing conducted, and are those workers compensated properly for their labour? Whose expertise is being modelled?
 - What are the goals set for AI systems? How is gender bias embedded into the algorithms? Who is considered the end user, whose user stories are being prioritised, and what is valued as success? What is being done to adjust the embedded bias of AI systems?
 - When developing AI systems, what value is given to the automatable tasks – and the roles that remain for humans when tasks are automated via machines, and what gender impact would there be?

AI use and implementation

- Are there barriers in place for certain groups/women in using AI tools, in terms of costs of buying systems, or biased perception when it is being used, time given to women to learn, etc? What is being done to address these barriers?
- When using AI tools in the organisation, for example for recruitment or performance evaluation, what patterns of bias are being amplified here? Is algorithmic management being introduced alongside these tools and what are the gender repercussions of this?
- When AI use is treated as a measure for performance evaluation, are individuals who have ethical or other concerns about AI being penalised – and how does this differ by gender and other demographic factors?
- When AI is used for training and education purposes (both at work but also in education systems), are these tools perpetuating gender biases?
- Who is made responsible when AI models/tools make errors? Who is held accountable and are there gender discrepancies in who is made to hold the risk?

Governance, accountability and voice

- When AI tools are replacing workers or augmenting jobs, are state policies sufficient in providing protection to ensure that everyone is protected? Are unions sufficiently supporting all workers' bargaining power?
- Are existing protections such as equality, employment and data protection law able to address potential AI harm? Even so, are gaps in social protection enough so to not exacerbate the unequal outcomes across the population? If not, why not and who is left behind? What systems are missing?
- Are the gendered effects of AI adoption being tracked at organisational and national level, and is anyone gathering or publishing the data? Who should be held accountable?
- Are there systems in place to ensure that those in the most vulnerable positions/sectors are included in the conversation?



Outputs of AI

- Who is able to benefit from the gains from AI and who is bearing the cost (environmental, labour market, political, etc.) of AI – is it gender equitable?
- How is the implementation of AI shaping how we value men's and women's work – especially with regards to care? Does the automation of tasks around care and relational work signal that these skills are technical and substitutable, and does this in turn depress the pay and status of the people who do them?
- How is the rise of AI shaping the gendered assumptions and bias – with regards to the images, information and other outputs it produces? Who is being excluded in the world depicted by AI and how does this reinforce bias against women and other vulnerable groups?

These questions are just the start of the questions we must ask and demand responses to when thinking of how to ensure the new age of AI does not result in increasing gender inequality patterns. The development of AI systems or any tech systems for that matter cannot be seen as deterministic (Wajcman, 1991a, 1991b, 2004). Technology is shaped by gender relations, and technologies in turn stabilise or reconfigure gender relations. We must acknowledge the human agency in this technological development and its impact and reflect on our decision-making processes to ensure AI advancement does not result in social inequalities. We must also question those who fail to reflect on their roles in exacerbating social inequalities and demand changes in the way it is introduced.

The future of work with AI does not necessarily have to be bleak for women or other minoritised groups. However, what is crucial at this critical juncture is to question the existing social inequalities and how AI interacts with them, to discuss the active role of the state in sharing both the risks and benefits of AI, and to proactively test and resist the biases embedded in and with AI.



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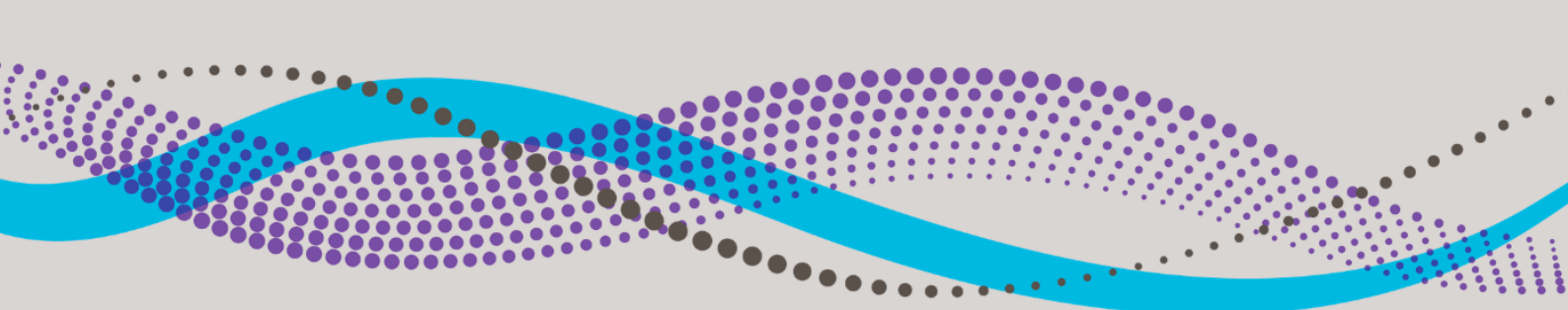
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