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Artificial Intelligence and Women's Economic Independence: Gender, Power, and Inequality in the Governance of AI

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Dedication

To the memory of Fereshteh Ahmadi, who was my age when she was killed during the Woman, Life, Freedom uprising in 2022.

To my mother, whose love and encouragement have always guided me, and whom I miss every day.

And to my father, with love and gratitude.

Abstract

Artificial intelligence is increasingly shaping access to employment, career progression, workplace evaluation and the distribution of economic opportunity. These developments raise a central question for gender equality: whether the governance of AI can support women's economic independence or reproduce the inequalities already embedded in labour markets and institutions. This thesis examines that question by analysing the relationship between AI governance, women's position in the changing world of work and the institutional conditions under which technological opportunities and risks are distributed. Women's economic independence is understood not simply as participation in paid work, but as the capacity to secure and sustain income, exercise economic choice and participate in economic life on equal terms.

The study combines feminist political economy, feminist technology studies, substantive equality, labour-market analysis and intersectionality. It reviews empirical research on representation in AI development and governance, employment opportunities, automation exposure, access to digital skills, algorithmic recruitment and management, and economic vulnerability. It then evaluates governance responses through international and European frameworks, including the European Union Artificial Intelligence Act, UNESCO instruments, the Council of Europe Framework Convention and CEDAW's approach to substantive equality. Illustrative regulatory and implementation examples from France and New York City are used to test how formal governance mechanisms operate in practice.

The analysis finds that AI may expand productive capacity and create new economic opportunities, but technological capability does not ensure that women can capture an equal share of those benefits. Existing occupational segregation, unequal access to authority, care responsibilities, stereotypes and differences in technological familiarity can shape both exposure to AI-related change and the ability to benefit from it. At the same time, algorithmic systems are not inherently discriminatory. Their effects depend on the objectives, data, comparison groups, deployment conditions and accountability mechanisms through which they are designed and used. Numerical representation is therefore relevant but insufficient when participation is not accompanied by decision-making authority, independent assessment and enforceable duties.

The thesis concludes that gender-responsive AI governance should be assessed through observable economic outcomes rather than the existence of principles or procedures alone.

Relevant benchmarks include access to employment opportunities, continuity and quality of work, wage and promotion patterns, meaningful participation in decisions, audit coverage, publication of findings and the availability of correction and remedy. It also identifies important limits in the available evidence. In particular, the relationship between AI-mediated work and women's exposure to intimate-partner or gender-based violence remains untested, and the regulatory examples considered are illustrative rather than proof of a universally effective governance model. The study therefore presents women's economic independence as a practical lens for evaluating whether AI governance responds to gendered inequalities in the labour market.

Keywords: artificial intelligence; AI governance; women's economic independence; gender equality; labour markets; algorithmic discrimination; substantive equality.

List of Abbreviations

AI	Artificial Intelligence
CEDAW	Convention on the Elimination of All Forms of Discrimination against Women
CoE	Council of Europe
EIGE	European Institute for Gender Equality
EU	European Union
FRIA	Fundamental Rights Impact Assessment
ICT	Information and Communication Technology
ILO	International Labour Organization
IMF	International Monetary Fund
IPV	Intimate Partner Violence
NIST	National Institute of Standards and Technology
NYC	New York City
OECD	Organisation for Economic Co-operation and Development
STEM	Science, Technology, Engineering and Mathematics
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organization

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Introduction

1.1 Background of the Study

Artificial Intelligence (AI) is no longer confined to research laboratories or the technology sector. It increasingly shapes decisions that influence everyday life, from recruitment and education to healthcare, finance, and public administration. As AI becomes embedded in economic and social systems, questions about who benefits from these technologies - and who may be left behind - have become central to contemporary debates on gender equality, public policy, and technological governance.

The rapid expansion of AI is transforming labour markets in unprecedented ways. AI technologies are changing how employees are recruited, evaluated, trained, and promoted, while also creating new forms of work and altering existing occupations. Research by the International Labour Organization suggests that the dominant effect of generative AI is more likely to be the augmentation of occupations than their complete automation, while also highlighting that exposure is highly gendered because clerical occupations represent an important source of female employment (Gmyrek et al., 2023). Existing inequalities in labour market participation, occupational segregation, and access to digital skills therefore suggest that women and men may experience the transition to an AI-driven economy differently.

At the same time, women continue to be underrepresented in technology and AI-related fields. The United Nations Educational, Scientific and Cultural Organization (UNESCO) reports that women account for only 22 per cent of professionals working in artificial intelligence and remain a minority in technical and leadership roles in technology companies (UNESCO, 2021). This underrepresentation is significant not only because it reflects existing inequalities within the technology sector, but also because the people who design, develop, and govern AI systems influence the priorities, assumptions, and values embedded within these technologies. Consequently, limited gender diversity in AI may affect both the design of AI systems and the social outcomes they produce.

These developments are closely linked to the broader issue of women's economic independence. Economic independence is a key dimension of the wider process of women's economic empowerment, which is shaped not only by access to income and employment but also by the social, policy, and economic environments in which women live and work (Breitkreuz et al., 2026). Access to decent work, equal career opportunities, financial resources, and digital skills can strengthen women's economic position and autonomy. As AI

increasingly shapes labour markets and future employment opportunities, understanding its implications for women's economic independence has become an important academic and policy concern.

In recent years, scholars and international organisations have devoted increasing attention to algorithmic bias, automation, AI ethics, and gender inequality in technology. Research on AI-supported recruitment, for example, shows that attempts to remove gender or race from automated hiring systems do not necessarily eliminate structural forms of inequality and may obscure the power relations within which such systems operate (Drage & Mackereth, 2022). At the governance level, international frameworks increasingly recognise the need to address the social and distributive effects of AI. UNESCO's Recommendation on the Ethics of Artificial Intelligence explicitly includes gender as well as economy and labour among its policy areas (UNESCO, 2021), while the OECD AI Principles call for trustworthy AI that advances inclusion and reduces economic, social, and gender inequalities (OECD, 2024d). These developments make the relationship between AI governance, women's economic position, and gender equality an increasingly important area of inquiry.

1.2 Research Aim and Objectives

Research Aim

The aim of this study is to examine how the governance of Artificial Intelligence (AI) influences women's economic independence and gender equality in the context of the changing world of work. As AI increasingly shapes labour markets, employment practices, and access to economic opportunities, understanding its implications for women has become an important academic and policy concern.

Although this research focuses primarily on women's economic independence, it approaches this concept as a key dimension of the broader process of women's economic empowerment - encompassing not only women's access to paid employment and financial resources, but also their ability to make autonomous economic decisions, access opportunities on equal terms, and participate fully in economic and social life.

Against this background, the study examines whether existing AI governance frameworks adequately address the gender-specific opportunities and challenges associated with AI-driven transformations. It further explores how more gender-responsive approaches to AI governance can contribute to strengthening women’s economic independence while promoting a more inclusive and equitable digital economy. The study also derives policy

implications for policymakers, businesses and educational institutions from the evidence and governance analysis. In doing so, the research seeks to contribute to current academic and policy debates on the relationship between AI governance, technological change and gender equality.

Research Objectives

To achieve this aim, the study pursues the following objectives:

- To examine the relationship between AI governance and women's economic independence.
- To analyse how AI-driven transformations of labour markets influence women's employment opportunities, career development, and economic security.
- To examine the relationship between women's numerical representation, substantive participation and decision-making authority in AI development and governance, and how these dimensions relate to the incorporation of gender perspectives into technological and policy processes.
- To analyse the mechanisms through which algorithmic decision-making may reproduce or intensify gender inequalities in access to employment, promotion and broader economic opportunities.
- To assess the extent to which existing AI governance frameworks incorporate gender equality considerations and respond to gender-specific challenges.
- To identify policy implications for strengthening gender-responsive AI governance in ways that support women's economic independence and advance gender equality.

1.3 Research Questions

The study is guided by the following research questions.

Main Research Question

How does the governance of Artificial Intelligence influence women's economic independence and gender equality in the changing world of work?

To answer this overarching question, the study addresses the following sub-questions:

1. How are women represented in the development, governance and regulation of Artificial Intelligence, and what is the relationship between numerical representation, substantive participation, decision-making authority and the incorporation of gender perspectives into AI policies and technological processes?

2. How do AI-driven transformations of labour markets affect women's employment opportunities, economic independence, and long-term economic security?

3. In what ways do algorithmic decision-making systems affect existing gender inequalities in employment and access to economic opportunities?

4. To what extent do current AI governance frameworks recognise and address the gender-specific challenges arising from AI-driven transformations?

5. How can more gender-responsive approaches to AI governance contribute to strengthening women's economic independence and promoting gender equality?

1.4 Significance of the Study

The rapid integration of Artificial Intelligence into labour markets and public decision-making has transformed AI from a purely technological innovation into an issue of significant social, economic, and policy relevance. AI can create opportunities for productivity and inclusion, but it can also produce uneven effects across occupations and social groups, including gendered effects in the labour market (Gmyrek et al., 2023; Collett et al., 2022). Understanding these developments is therefore important for ensuring that technological progress contributes to more inclusive and equitable societies.

From an academic perspective, this study is significant because it examines the intersection of several debates that are directly relevant to the future of work: AI governance, gendered labour-market change, algorithmic decision-making, and women's economic empowerment. The joint UNESCO, IDB, and OECD report on the working lives of women demonstrates the importance of examining AI across the employment lifecycle, from job requirements and hiring to career progression and upskilling (Collett et al., 2022). Building on these concerns, this study places women's economic independence at the centre of the analysis and considers how governance choices shape the opportunities and risks associated with AI-driven transformation.

The study is equally significant from a policy perspective. International governance frameworks increasingly emphasise trustworthy, human-centred, and accountable AI. UNESCO's global Recommendation identifies gender and economy and labour as distinct areas for policy action (UNESCO, 2021), while the OECD AI Principles explicitly connect trustworthy AI with inclusion, equality, fairness, and internationally recognised labour rights (OECD, 2024d). Examining these commitments through the lens of women's economic

independence may therefore provide useful insights for policymakers seeking to translate broad governance principles into more gender-responsive labour-market outcomes.

Finally, this study has broader social significance. Women's economic empowerment is closely connected to gender equality and is shaped by the institutional, social, and economic conditions that can enable or constrain women's wellbeing and economic participation (Breitkreuz et al., 2026). By examining how AI governance interacts with these conditions, this study aims to contribute to debates on how the digital economy can expand women's opportunities and autonomy while limiting new or intensified forms of inequality.

1.5 Novelty of the Study

The principal contribution of this study is its sustained use of women’s economic independence as an organising lens for evaluating AI governance. Building on scholarship that already moves beyond numerical representation and bias within individual systems, the thesis connects technological change to the full economic pathway through which opportunities may become—or fail to become—secure work, income, professional advancement, bargaining power and longer-term economic autonomy.

A second contribution is the distinction between the availability of technological opportunity and women’s capacity to capture and convert that opportunity into durable economic benefit. This distinction brings together evidence on productivity, occupational exposure, skills, algorithmic decision-making and financial security without assuming that access to an AI tool or employment opportunity is equivalent to economic empowerment.

The thesis also identifies the allocation of institutional responsibility as a cross-cutting governance issue. It asks who bears the burden of detecting, explaining and correcting unequal outcomes and whether governance follows the economic pathway across visibility of opportunities, selection, working conditions, advancement and occupational transition. The French regulatory decision and evidence concerning New York City’s audit regime are used illustratively to test these questions rather than to claim a universally validated governance model.

1.6 Structure of the Thesis

The thesis is organised into four main chapters in addition to the Introduction. The Introduction presents the background of the study, its research aim and objectives, the research questions, the significance and novelty of the research, and the overall structure of the thesis.

Chapter 1, Artificial Intelligence and the Transformation of Work, constructs the conceptual and theoretical framework used throughout the thesis. It defines the central concepts—AI governance, women's economic independence, gendered labour-market inequality, automation exposure, the digital divide, algorithmic bias and economic vulnerability—and specifies how feminist political economy, feminist technology studies, human capital theory, labour-market segmentation and intersectionality guide their interpretation. The chapter does not seek to catalogue the prevalence or magnitude of the relevant labour-market patterns. Empirical findings appear only to establish the conceptual stakes, identify competing explanations and delimit claims that the thesis can reasonably make. The systematic mapping of evidence and institutional instruments is reserved for Chapter 2.

Chapter 2, AI Governance, Gender Equality, and Women's Economic Independence, applies the concepts established in Chapter 1 to map the evidentiary and institutional landscape within which AI governance operates. It organises empirical research and legal or policy materials across representation, decision-making power, employment opportunity, job displacement, access to skills, algorithmic workplace decisions, financial security and existing governance frameworks. Its distinct function is descriptive and evidentiary: it establishes what the available evidence shows, distinguishes direct findings from inference and identifies the limits that the later governance analysis must respect.

Chapter 3, Gendered Power Relations in the Governance of AI, builds on this mapping by examining the distribution of power and institutional responsibility and by evaluating whether existing governance arrangements respond adequately to the patterns identified in Chapter 2. It uses illustrative regulatory decisions and implementation evidence to test broader governance claims and develops the implications for human rights, social justice, policymakers, businesses and educational institutions.

Finally, Chapter 4, Conclusion, brings together the main findings of the study, answers the research questions, and presents the principal conclusions arising from the analysis.

1.7 Declaration on the Use of Artificial Intelligence Tools

During the preparation of this thesis, ChatGPT and Claude were used to assist with the revision of selected passages and the identification of potential academic sources. AI-generated suggestions were not incorporated automatically, and the author assumes full responsibility for the final work.

Chapter 1

Artificial Intelligence and the Transformation of Work

This chapter constructs the conceptual and theoretical framework through which the thesis analyses AI governance and women's economic independence. It defines the principal concepts, distinguishes relationships that can be examined from causal claims that the available evidence cannot establish, and sets out the theoretical lenses used to interpret later findings. The chapter is therefore organised by analytical questions rather than by an attempt to measure the prevalence of each labour-market pattern. Evidence and examples are included only where they clarify why a concept matters, reveal a competing explanation or establish the boundary of a claim. Chapter 2 then applies this vocabulary to map the empirical and institutional evidence across the employment pathway; Chapter 3 uses that map to evaluate power, institutional responsibility and the adequacy of governance responses. This division of labour prevents the conceptual discussion in Chapter 1 from functioning as a preliminary version of the evidence review that follows.

1.1 AI Governance and Gendered Power Relations

Artificial Intelligence governance has emerged as an important field of research and policy as AI systems have become increasingly integrated into economic, institutional, and social decision-making. In broad terms, AI governance refers to the structures, processes, policies, and mechanisms through which the development and use of AI are directed and overseen. It can operate at different levels, including organisations, industries, national governments, and international institutions, and may involve regulatory frameworks, ethical principles, technical standards, and mechanisms of accountability. A systematic review of the literature on AI governance shows that governance involves not only how AI is regulated, but also who participates in governing it, what elements of AI systems are governed, and at which stages of the AI life cycle governance mechanisms are applied (Batool et al., 2025). AI governance should therefore be understood as a broader institutional process rather than simply as the adoption of technical rules or legal regulation.

This broader understanding is particularly important when AI governance is examined from a gender perspective. Decisions concerning the design, development, regulation, and deployment of AI are made within existing social and institutional structures rather than in a neutral environment. The actors involved in these processes have different levels of access to resources, expertise, institutional authority, and decision-making power. Consequently, questions about AI governance are also questions about participation and power: who is able to influence technological development, whose interests are represented in governance

processes, and whose experiences are considered when the potential benefits and harms of AI systems are assessed.

Feminist approaches to AI governance draw particular attention to these questions. Ricaurte (2024) argues that AI systems should be understood as sociotechnical systems shaped by economic, historical, political, legal, and cultural contexts. From this perspective, inequalities associated with AI cannot be understood solely as technical problems located within algorithms or datasets. They must also be examined in relation to the structures of power surrounding the production and governance of technology. Feminist AI governance therefore places emphasis on structural inequalities, unequal representation, and power asymmetries across the AI ecosystem, while asking how governance arrangements might become more participatory and responsive to communities that have traditionally had less influence over technological decision-making.

Recent scholarship develops this argument further by examining participation and exclusion within AI governance itself. Attard-Frost (2025), for example, argues that large-scale AI governance systems may reproduce power imbalances when the interests and resources of dominant state and industry actors have greater influence than those of marginalised communities. This perspective is important because it shifts attention from the outcomes produced by individual AI systems to the institutional arrangements through which AI is governed. Gender inequality in AI is therefore not only a question of whether an algorithm produces discriminatory results. It also concerns who has the authority to define acceptable risks, establish governance priorities, participate in regulatory processes, and determine which forms of knowledge and experience are considered relevant.

These concerns are also increasingly visible in debates surrounding AI regulation. A feminist analysis of the European Union's Artificial Intelligence Act, for instance, argues that although the regulatory framework contains mechanisms intended to address discrimination and gender-related risks, questions remain about its capacity to respond to structural inequalities and systemic power imbalances (Karagianni, 2025). Preventing discriminatory outputs from individual AI systems is an important component of responsible governance, but a gender-responsive approach requires attention to the wider institutional conditions in which technologies are developed and regulated. It therefore requires consideration of representation, participation, accountability, and the distribution of decision-making power throughout the AI life cycle.

For the purposes of this study, gendered power relations in AI governance refer to the ways in which unequal access to technological, economic, and institutional decision-making may shape the development and governance of AI and, consequently, its social and economic effects. This approach does not assume that AI governance necessarily reproduces gender inequality. Rather, it provides a framework for examining the conditions under which governance structures may reinforce existing inequalities or contribute to more inclusive outcomes. This distinction is particularly relevant to women's economic independence, because governance decisions concerning employment-related AI, access to digital opportunities, algorithmic decision-making, and future labour-market transitions may ultimately influence women's ability to participate in economic life on equal terms.

Women's participation in the AI sector provides an important illustration of these unequal distributions of influence. UNESCO reports that women account for approximately 30 per cent of professionals in the broader AI sector, while their representation is lower in several positions associated with research and leadership (UNESCO, 2024). This gap matters for AI governance because participation in the AI workforce and participation in positions of authority are not necessarily the same. Increasing the number of women working in AI is important, but numerical representation alone does not ensure that women have equal influence over strategic decisions concerning technological development, investment priorities, organisational practices, or the governance of AI systems.

The distinction between representation and decision-making power becomes even more significant at the policy level. UNESCO's Women for Ethical AI: Outlook Study on Artificial Intelligence and Gender reports substantial gaps in the incorporation of gender perspectives into AI governance. Among 138 countries assessed through the Global Index on Responsible AI, only 24 had frameworks that mentioned gender, and only 18 made a significant reference to gender issues in relation to AI (UNESCO, 2024). The report further notes that gender equality and women's empowerment remain underrepresented in AI governance discourse and practice. These findings suggest that increasing women's participation in technical fields is only one dimension of gender-responsive AI governance. Attention must also be given to whether gender perspectives are incorporated into the institutions, policies, and regulatory processes through which AI priorities and responsibilities are established.

Effective involvement therefore requires more than the physical presence of women within technological institutions. It also concerns the capacity to influence decisions, define priorities, identify risks, and participate in the development of governance frameworks. This distinction is reflected in UNESCO's Women4Ethical AI initiative, whose objectives include

strengthening women's participation and leadership across AI education, research, development, and governance, as well as promoting the integration of gender perspectives into AI governance and policy frameworks (UNESCO, n.d.). A gender-responsive approach to governance therefore involves both representation and the ability to exercise influence over decisions throughout the AI system life cycle.

At the same time, the relationship between representation and gender equality should not be treated as automatic. The presence of more women in AI institutions does not by itself guarantee gender-responsive technologies or policies. Women are not a homogeneous group, and their experiences are shaped by differences in class, race, ethnicity, disability, migration status, geographical location, and other social conditions. A focus on representation must therefore be accompanied by attention to the distribution of institutional power and to whose perspectives are actually able to influence technological and regulatory choices. From this perspective, gender-responsive AI governance is concerned not simply with bringing more women into existing structures, but also with examining whether those structures allow diverse groups of women to participate substantively in decisions that may affect them.

This issue becomes especially important when AI governance is connected to the changing world of work. Research examining the effects of AI on women's working lives shows that AI may affect women at multiple stages of the employment lifecycle, including recruitment, career progression, and opportunities for upskilling (Collett et al., 2022). Women's limited representation within parts of the AI ecosystem and the limited incorporation of gender perspectives into many governance frameworks therefore raise a broader question for this study: whether AI governance arrangements are capable of recognising and responding to the different ways in which technological change may affect women's position in the labour market.

Gendered power relations thus provide an important bridge between AI governance and women's economic independence. The central issue is not simply whether women are present in the AI sector, but whether governance structures provide meaningful opportunities for women to influence decisions that shape technological and economic change. Examining representation alongside decision-making power allows this study to consider AI governance as both a potential site of inequality and a possible mechanism for promoting more inclusive outcomes. This provides the foundation for the following section, which examines women's economic independence in relation to persistent inequalities in the labour market.

1.2 Women's Economic Independence and Labour Market Inequality

Women's economic independence is closely connected to, but should not be treated as identical with, the broader concept of women's economic empowerment. Women's economic empowerment encompasses women's ability to participate in and benefit from economic life on equal terms, exercise agency, control resources and income, benefit from decent work and social protection, and participate in economic decision-making (UN Women, 2024). It is therefore a multidimensional concept that extends beyond labour-force participation or access to paid employment. Recent scholarship similarly emphasises the importance of examining what is meant by the "economic" dimension of women's empowerment and how it is measured, rather than reducing empowerment to a single labour-market outcome (Robbenhaar et al., 2026).

Within this broader framework, economic independence can be understood as a key dimension of women's economic empowerment, particularly in relation to the ability to secure economic resources and exercise autonomy over economic decisions. This distinction is important because employment does not necessarily translate into economic independence. A woman may participate in paid work while remaining economically vulnerable if her employment is insecure, poorly paid, informal or unpredictable, or if it provides insufficient access to social and labour protections. The International Labour Organization has similarly emphasised that women's economic empowerment depends not only on access to paid employment but also on its quantity and quality, the provision of public services, the burden of unpaid care work, and access to social and labour protections (ILO, 2017). Economic independence should therefore be considered in relation to the security, quality and conditions of employment, rather than through employment status alone.

This distinction becomes particularly important when women's position in the labour market is considered. Despite progress in women's labour-force participation, substantial gender inequalities remain. Globally, the labour-force participation rate of women aged 25–54 increased from 62.8 per cent in 2015 to 64.5 per cent in 2024, while the gender gap remained 27.8 percentage points. Persistent barriers include pay inequalities, occupational segregation, limited opportunities for leadership and unequal caregiving responsibilities (UN Women & UN DESA, 2025). These patterns indicate that participation in the labour market does not in itself guarantee equal access to economic security, advancement or autonomy.

The quality and formality of employment are also relevant to economic independence. Informal employment is frequently associated with lower wages, unsafe working conditions

and limited access to social protection. UN Women further notes that women in informal employment may experience limited voice and legal recognition, while inadequate pension coverage can contribute to economic insecurity later in life (UN Women, 2024). Consequently, paid work can provide an immediate source of income without necessarily ensuring longer-term financial security or autonomy. This reinforces the need to distinguish between women's participation in employment and the conditions under which employment can contribute to sustainable economic independence.

Unpaid care responsibilities constitute another structural constraint on women's economic independence. The unequal distribution of care work can affect women's ability to enter and remain in paid employment and can restrict the range of employment opportunities available to them. ILO estimates indicate that in 2023, 708 million women worldwide were outside the labour force because of unpaid care responsibilities, compared with 40 million men (ILO, 2024). Care responsibilities can therefore shape not only labour-force participation but also women's capacity to pursue stable employment and maintain economic security over time. Addressing economic independence consequently requires attention to the social and institutional arrangements that influence the distribution of paid and unpaid work.

Occupational segregation represents a further dimension of labour-market inequality. Women and men continue to be distributed unevenly across occupations, with important consequences for earnings, career progression and exposure to economic change. These patterns are particularly relevant to this study because technological transformation does not occur independently of existing labour-market structures. Recent ILO research demonstrates that occupational segregation also shapes patterns of exposure to generative AI: female-dominated occupations are almost twice as likely to be exposed to GenAI as male-dominated occupations, at approximately 29 per cent compared with 16 per cent (ILO, 2026). Women also remain underrepresented in AI-related occupations, which may limit their access to some of the emerging opportunities associated with technological change.

These findings do not mean that AI exposure necessarily results in job displacement. For many occupations, the effects of generative AI are expected to occur through changes in tasks, skills requirements and working conditions rather than through the complete elimination of jobs (ILO, 2026). This distinction is especially significant when women's economic independence is used as the analytical lens. The relevant question is not only whether women remain employed as AI becomes more widely adopted, but also how technological change may affect the quality, security and future prospects of their employment.

From this perspective, labour-market inequality constitutes an important context within which AI governance operates. AI is being introduced into labour markets already characterised by gender differences in occupational distribution, care responsibilities, employment conditions and access to economic opportunities. AI governance cannot by itself eliminate these broader structural inequalities, but governance and policy choices can influence how the risks and opportunities associated with technological transformation are distributed. Recent ILO research stresses that policy choices, social dialogue, efforts to address occupational segregation and women's representation in AI-related roles will be important in determining whether technological change advances or reinforces existing gender inequalities (ILO, 2026).

For this study, these unequal starting conditions are central to understanding the relationship between AI governance and women's economic independence. Evaluating AI governance solely in terms of employment creation or technological innovation would provide an incomplete picture of its gendered economic implications. A gender-responsive approach must also consider whether governance frameworks recognise differences in employment security, care responsibilities, occupational position and access to emerging economic opportunities. Women's economic independence therefore provides a broader evaluative lens through which the effects of AI-related policies and governance arrangements can be examined. Against this background, the following section considers more specifically how AI and automation may transform women's work and their position within changing labour markets.

1.3 AI, Automation, and the Future of Women's Work

The rapid diffusion of Artificial Intelligence, and particularly generative AI, has intensified debates about the future of work. Much of this debate has focused on whether AI will replace human labour, create new employment opportunities, or transform existing occupations. However, the relationship between AI and employment is more complex than a simple distinction between job creation and job loss. Occupations are composed of multiple tasks, and AI may automate some of these tasks while complementing or transforming others. For this reason, occupational exposure to AI should not be interpreted as equivalent to job displacement. Recent ILO research emphasises that exposure measures identify the extent to which tasks within occupations may potentially be affected by AI, but do not by themselves determine actual employment outcomes (Gmyrek et al., 2025).

This distinction is particularly important in the context of generative AI. The ILO's refined global index of occupational exposure estimates that approximately one in four workers worldwide are employed in occupations with some degree of exposure to generative AI. At the same time, the study concludes that job transformation is more likely than widespread replacement because most occupations continue to involve tasks requiring human input (Gmyrek et al., 2025). The likely effects of AI should therefore be understood in terms of changing task composition, working methods, productivity, skill requirements and employment conditions, rather than solely in terms of whether occupations disappear.

The concepts of automation and augmentation are useful for understanding these different pathways. Automation occurs when AI performs tasks that were previously undertaken by workers, potentially reducing the amount of human labour required. Augmentation, by contrast, occurs when AI supports workers in performing tasks more efficiently or effectively. The extent to which an occupation is exposed to AI does not determine which of these outcomes will occur. Cazzaniga et al. (2024) distinguish between AI exposure and AI complementarity, noting that some highly exposed occupations may benefit from productivity gains when AI complements human capabilities, while occupations with lower complementarity may face greater risks of task substitution or reduced labour demand.

These dynamics have particular implications for women because women and men are not distributed equally across occupations. As discussed in the previous section, occupational segregation contributes to different patterns of exposure to technological change. Women are strongly represented in many clerical, administrative and service-related occupations in which a relatively high proportion of tasks may be affected by generative AI. ILO research also finds that female employment is more concentrated than male employment in the highest exposure category, particularly in higher-income countries (Gmyrek et al., 2025). This does not mean that women will necessarily experience greater job losses, but it indicates that changes in task composition and working practices may affect women differently.

At the same time, greater exposure to AI may also create opportunities. The IMF notes that women are, in many countries, more concentrated in occupations with relatively high AI exposure, but that some of these occupations also have considerable potential for complementarity. Women may therefore benefit from productivity gains or the transformation of existing roles where AI is used to support rather than replace human labour (Cazzaniga et al., 2024). This dual possibility is important because it challenges the assumption that greater exposure should automatically be interpreted as greater vulnerability. The economic

consequences of AI depend in part on whether workers are able to access and use technologies in ways that enhance their productivity and labour-market position.

However, the potential benefits of AI may not be distributed equally. OECD research highlights gender differences not only in exposure to AI but also in access to AI-related employment and productivity-enhancing tools. In one study discussed by the OECD, women were around 20 percentage points less likely than men working in the same occupation to report having used ChatGPT. Although the use of a single AI tool cannot capture the full gender gap in AI adoption, the finding illustrates a broader concern: women may be exposed to changes generated by AI while having less access to some of the tools and opportunities through which its benefits are realised (OECD, 2024a).

This possibility has important implications for job quality and economic independence. If AI is primarily used to complement workers, it may contribute to higher productivity, improved efficiency and the reduction of repetitive tasks. Yet the transformation of work may also alter workloads, expectations, skill requirements and employment security. The ILO therefore cautions against treating technological transformation exclusively as a question of employment quantity. AI adoption can also influence the quality and organisation of work, meaning that its effects should be assessed in relation to working conditions as well as employment levels (International Labour Organization, 2025). For women, whose economic independence may already be affected by unequal employment conditions, changes in the quality and security of work are particularly relevant.

The effects of AI on women's work are therefore unlikely to be uniform. Women in different occupations, sectors and national contexts may encounter different combinations of automation risk, augmentation potential and access to emerging opportunities. Furthermore, exposure does not automatically determine outcomes, because the adoption and use of AI depend on organisational practices, infrastructure, workforce capabilities and policy choices. The ILO's analysis of gender and generative AI emphasises that current policy choices—including social dialogue, efforts to address occupational segregation and women's representation in AI-related roles—will play an important role in determining whether technological change supports gender equality or reinforces existing inequalities (ILO, 2026).

The future of women's work under AI should consequently be understood not simply as a technological question, but also as a governance question. AI governance can influence the conditions under which technologies are introduced into workplaces, how labour-market transitions are managed, and how the benefits and risks of technological change are

distributed. Regulatory frameworks, social protection, labour-market policies, social dialogue and support for workforce adaptation can all shape whether AI contributes to more secure and productive employment or increases existing forms of economic vulnerability. Cazzaniga et al. (2024), for example, argue that governments will need to strengthen regulatory frameworks, support labour reallocation and protect workers who may be adversely affected by AI-driven change.

For the purposes of this study, the central question is therefore not whether AI will simply ‘replace’ women’s jobs. A more relevant question is how AI-driven changes in tasks, productivity, working conditions and employment opportunities interact with women’s existing labour-market position and economic independence. The future of women’s work will depend not only on the technical capabilities of AI, but also on the institutional and policy choices through which technological change is governed. This provides the basis for the following section, which examines another important dimension of this relationship: unequal access to digital technologies and AI-related skills.

1.4 The Gender Digital Divide and Unequal Access to AI-Related Skills

The expansion of Artificial Intelligence in the workplace makes access to digital technologies and relevant skills increasingly important for workers’ ability to adapt to technological change. Yet access to these resources remains uneven. The gender digital divide has traditionally been discussed in terms of differences in access to the internet, digital devices and connectivity. These inequalities have not disappeared: in 2025, 71 per cent of women globally used the internet compared with 77 per cent of men, leaving approximately 280 million more men than women online (International Telecommunication Union [ITU], 2025). The size of this divide also varies substantially across regions and levels of economic development, indicating that women’s participation in the digital economy is shaped by wider social and economic conditions rather than by technology alone.

Connectivity, however, represents only one dimension of the contemporary digital divide. As digital technologies become more sophisticated, the ability to use them effectively becomes increasingly significant. In many OECD countries, gender differences in basic online activities have become relatively small, while inequalities remain more visible in advanced digital skills and participation in the development of new technologies. The OECD reports that women remain underrepresented among ICT specialists and professionals with AI skills. Women also remain underrepresented in AI research: in 2023, less than 40 per cent of AI-related scientific publications across OECD countries were co-authored by women, while men

contributed to approximately 90 per cent of such publications (OECD, 2024b). These patterns suggest that narrowing the gap in basic digital access does not necessarily produce equal participation in the areas where emerging technologies are developed and shaped.

A similar pattern can be observed in education and employment. UNESCO reports that women constitute approximately 35 per cent of STEM graduates globally. Women are also substantially underrepresented in data- and AI-related employment, accounting for around 26 per cent of the workforce in these fields (UNESCO, 2025). These figures should not be interpreted as evidence of an inherent difference in technological ability between women and men. Rather, they point towards unequal pathways into fields that increasingly influence employment opportunities in the digital economy. Educational opportunities, social expectations, access to training and the structure of labour markets can all affect who develops advanced digital capabilities and who subsequently enters technology-related occupations. The gender digital divide therefore involves not only access to technology, but also unequal opportunities to acquire, apply and benefit from relevant skills.

At the same time, the meaning of "AI-related skills" should not be restricted to highly specialised technical knowledge. Only a relatively small proportion of workers will need to develop or maintain AI systems directly. Recent ILO research shows that the wider transformation of work is increasing the importance of a broader combination of capabilities, including general digital and AI skills, higher-order cognitive and socioemotional skills, AI literacy, adaptability and human agency (Bardak et al., 2026). Similarly, OECD research identifies foundational knowledge, digital capabilities and complementary skills such as critical thinking, creativity and collaboration as increasingly relevant to workers' ability to interact effectively with AI systems (OECD, 2024b). This broader understanding matters for gender equality because participation in an AI-influenced labour market will not depend solely on whether women enter technical AI professions; it will also depend on whether women across occupations are able to use and adapt to AI as it becomes integrated into their work.

This creates a two-sided challenge for women's position in the changing labour market. As argued in the previous section, exposure to AI does not itself imply job displacement. Nevertheless, workers who have fewer opportunities to acquire and use relevant skills may find it more difficult to adapt when tasks and job requirements change. At the same time, unequal access to these skills may prevent workers from benefiting from AI even where the technology complements rather than replaces human labour. The gender skills gap can therefore operate in two directions: it may increase vulnerability to some forms of AI-driven

labour-market transformation while simultaneously limiting access to the productivity gains and new economic opportunities that AI can generate.

Evidence on access to AI-related opportunities reinforces this concern. OECD research finds that the workforce with the skills required to develop and maintain AI systems remains small and is disproportionately male and university educated. The same research warns that women and workers with lower levels of education may have less access both to AI-related employment and to productivity-enhancing AI tools in the workplace (Lane, 2024). A related OECD policy brief reports that, in one study, female workers were 20 percentage points less likely than male workers in the same occupation to report having used ChatGPT (OECD, 2024a). The finding should be interpreted cautiously, since the use of one generative AI tool cannot represent women's access to AI as a whole. Nevertheless, it illustrates how unequal access to emerging technologies may influence who is positioned to benefit from them at work.

For this study, these inequalities are particularly relevant because access to skills is connected to economic independence through more than employability alone. If AI-related capabilities increasingly affect workers' ability to adapt to changing occupations, access higher-value tasks, improve productivity or enter emerging areas of employment, unequal opportunities to develop those capabilities may also affect women's longer-term economic security and autonomy. Conversely, improving access to appropriate education and training may strengthen women's capacity to respond to technological change and take advantage of new forms of employment. The relationship is therefore not simply between skills and jobs, but between access to skills and the ability to participate in economic transformation on more equal terms.

This perspective also brings the discussion back to AI governance. Skill inequalities are not fixed outcomes of technological development. Governments, educational institutions, employers and other actors can influence access to digital education, AI literacy, vocational training, reskilling and lifelong learning. The ILO argues that preparing workers for AI requires modernising skills systems and equipping workers with digital and AI capabilities, while recent OECD analysis similarly stresses the role of education and training policies in ensuring that workers can benefit from AI-driven change (Bardak et al., 2026; OECD, 2024b). From a gender perspective, however, expanding training opportunities alone may not be sufficient if existing barriers continue to shape who can access, complete and benefit from them. Gender-responsive approaches therefore need to consider not only the availability of

skills programmes, but also whether women have meaningful opportunities to participate in them and translate acquired skills into employment and economic benefits.

The gender digital divide is thus relevant to AI governance because it influences the distribution of both technological risks and technological opportunities. Women who lack equal access to digital infrastructure, AI-related skills and opportunities to use emerging technologies may face greater difficulty adapting to changes in work while also being less able to benefit from productivity gains and new forms of employment. Addressing these inequalities is therefore part of creating conditions in which AI can contribute to women's economic independence rather than deepen existing economic disparities. Access to technology and skills, however, does not by itself guarantee equality. Even women who possess the necessary qualifications may encounter discriminatory outcomes when algorithmic systems are used in recruitment, evaluation and other employment decisions. This problem is examined in the following section.

1.5 Algorithmic Bias and Gender-Based Discrimination

Algorithmic discrimination should not be understood as an autonomous action of Artificial Intelligence. AI systems operate according to objectives, data choices and programming decisions defined by human actors and are introduced into workplaces through organisational and institutional decisions. This makes the way such systems are designed and governed particularly important. Berg and Johnston (2025), in their analysis of AI in human resource management, identify three elements that require attention: the objective a system is intended to achieve, the data on which it relies and the way it is programmed. Their analysis covers applications in recruitment, compensation, scheduling and performance management, showing that concerns about algorithmic bias extend beyond the training dataset itself.

Data nevertheless remain an important part of the problem, particularly when AI systems are introduced into labour markets that are already unequal. As discussed in Section 1.2, women and men are not equally distributed across occupations and continue to experience differences in pay, employment conditions and access to economic opportunities. Historical employment data have been produced within these conditions. Treating such data as a neutral record of merit or performance can therefore be problematic. Past patterns can enter automated decision-making through the information selected for analysis, the outcomes a system is designed to predict or the indicators used as proxies for more complex characteristics.

The same concern applies to the objectives assigned to these systems. An organisation decides what an AI application should optimise and which characteristics should count as evidence of suitability, productivity or performance. Programming choices then translate those decisions into a system that can influence employment outcomes (Berg & Johnston, 2025). The relevant question is not whether an algorithm itself intends to discriminate; it has no such independent intention. Attention instead needs to be directed towards the choices surrounding its development and use, and towards who is responsible for examining their consequences.

This becomes particularly significant when automated systems participate in decisions about hiring, pay, working schedules, performance evaluation and career progression. These decisions affect more than access to a particular job. They shape income, employment security and opportunities for advancement. For women, repeated disadvantage in these areas can weaken the conditions required for economic independence. Algorithmic bias is relevant to this study not simply as a question of technical fairness, but because the governance of employment-related AI can influence access to economic opportunities.

The EU Artificial Intelligence Act provides a useful indication of how seriously these risks are regarded at the regulatory level. Under Regulation (EU) 2024/1689, specified AI systems used for recruitment and selection and for certain decisions concerning work-related relationships, task allocation, monitoring and evaluation are classified as high-risk. Recital 57 links these applications to career prospects, livelihoods and workers' rights and specifically recognises the possibility of perpetuating historical patterns of discrimination, including discrimination against women. The classification is relevant here as evidence that employment-related algorithmic discrimination has become an AI governance concern. A fuller assessment of the Act and its treatment of gender equality is reserved for Section 2.8.

None of this means that the use of AI necessarily produces more discrimination. The European Commission notes that appropriately designed and used AI systems can also contribute to reducing bias and existing structural discrimination (European Commission, n.d.). This possibility is important because human decision-making in employment is not itself free from prejudice. The comparison is therefore not between biased algorithms and neutral human decision-makers. What matters is how particular systems are designed, what evidence is used to assess their effects and what safeguards apply when they are deployed.

For high-risk systems, the EU framework addresses some of these questions through requirements concerning risk management, data quality, documentation, traceability and

human oversight. The Commission also points to sufficiently representative datasets and mechanisms for detecting, correcting and mitigating unfair bias (European Commission, n.d.). These safeguards illustrate the role of governance at different stages of an AI system's use. Responsibility cannot be transferred to the technology simply because a decision has been automated.

For the purposes of this study, this last point is central. Women may have the qualifications and AI-related skills discussed in Section 1.4 and still encounter unequal economic outcomes if the systems involved in allocating employment opportunities reproduce existing inequalities. At the same time, such outcomes are neither predetermined nor an unavoidable consequence of AI. They depend in part on choices about design, deployment, oversight and accountability. The question is one of governance: under what conditions can the use of AI support more equal employment decisions, and under what conditions does it allow existing inequalities to persist or operate at greater scale?

1.6 Economic Dependency and Gender-Based Vulnerability

Economic independence has implications that extend beyond women’s position in the labour market. As discussed earlier in this chapter, paid employment does not necessarily amount to economic independence. Income matters, but so do accumulated resources and the ability to exercise control over economic decisions. EIGE’s multidimensional approach to financial independence reflects this distinction by considering income, wealth, and power and control rather than earnings alone (European Institute for Gender Equality [EIGE], 2024). This broader understanding is relevant when economic resources shape the choices available to women in their private as well as their working lives.

Economic dependency should not, however, be treated as a direct cause of gender-based violence. Women who are employed or financially independent may also experience violence. The World Health Organization (WHO, 2026) describes intimate partner and sexual violence as arising from the interaction of factors at individual, relationship, community and societal levels. Economic circumstances can form part of this wider context, but they do not provide a single explanation for why violence occurs.

The importance of economic dependency lies partly in the constraints it can place on women’s choices. EIGE links financial dependence to different forms of violence, including economic violence, and connects financial independence with access to resources and decision-making power (EIGE, 2024). More recent EIGE evidence notes that a lack of financial resources is a major barrier to leaving abusive relationships (EIGE, 2026). Economic

independence cannot eliminate the risk of violence, but access to independent resources can matter when a woman needs to make decisions about housing, everyday expenses, safety or leaving a relationship.

The relationship can also operate in the opposite direction. Economic violence may itself undermine economic independence. EIGE (2026) describes practices such as controlling money, restricting access to work or education, withholding funds, interfering with bank accounts, taking wages or benefits, and creating debt in another person's name. These practices show why economic dependency and gender-based vulnerability should not be arranged as a simple one-way causal chain. Economic control can weaken autonomy, while limited independent resources can make it harder to leave situations in which that control occurs.

AI enters this relationship through its effects on the material conditions of independence. Changes in job security, earnings, scheduling, career progression, privacy or access to work can expand or restrict the resources and choices available to women. The evidence reviewed here does not establish that AI-mediated work affects intimate-partner or gender-based violence differently from other forms of work. It establishes a more limited point: employment conditions shaped by AI may alter the economic options available within situations of dependency or control.

Section 1.6 therefore adds a dimension not covered by the earlier account of labour-market inequality. The issue is not only whether women obtain employment or income, but whether they retain control over resources and sufficient economic room to make decisions outside the workplace. Governance analysis should accordingly examine whether AI deployment changes employment continuity, income control, workplace surveillance, privacy or access to remedy. Economic independence is neither a guarantee of safety nor a complete explanation of violence; it is one condition that can widen or narrow the choices available to women facing economic control.

1.7 AI as a Tool for Gender Equality

The potential of AI to contribute to gender equality depends partly on who is able to participate in the technological transformation surrounding it. Women's participation cannot be considered only at the point at which AI-related jobs become available. Gender differences in access to technology, education and professional opportunities develop much earlier and can shape who eventually enters technological fields. Women currently represent around 35 per cent of STEM graduates globally (UNESCO, 2025), while persistent gender stereotypes

and unequal access to educational opportunities continue to affect girls' participation in these fields (UNESCO, 2026).

This matters because AI is developing within a technological sector in which women are already underrepresented. The problem is therefore broader than whether women receive specific training to use individual AI tools. Girls and women need genuine opportunities to study, work and progress in technological fields if they choose to do so. The OECD identifies stereotyping, a lack of female role models, discrimination in recruitment and unfavourable working conditions among factors that can contribute to gender divides in technology and STEM (OECD, 2024a). These barriers can accumulate over time and shape women's access to sectors increasingly connected to the development and use of AI.

The consequences are also visible in the emerging AI economy. Women remain underrepresented in AI-related employment, limiting their access to emerging opportunities and influencing how technologies are designed and deployed (ILO, 2026). This does not mean that participation in AI occupations should become an expectation for women, nor that AI-related skills provide a guaranteed route to economic independence. The concern is more basic: unequal access to expanding areas of employment can become another dimension of existing labour-market inequality. Equal opportunity requires that women are not excluded because of stereotypes, educational barriers or unequal conditions of entry and progression.

This shifts part of the discussion from individual adaptation to the conditions surrounding technological change. Asking women simply to adapt after inequalities in education and employment have already developed places too much responsibility on individuals. UNESCO's Women4Ethical AI initiative takes a broader approach. Its objectives include gender-responsive policy and funding, measures addressing structural gender gaps, and stronger participation and leadership of women across AI education, research, development and governance. UNESCO also encourages targeted programmes to increase opportunities for girls and women in STEM and ICT disciplines (UNESCO, n.d.).

Participation is relevant not only to employment opportunities but also to the development and governance of AI itself. Greater inclusion of women across technological education, research, development and decision-making can broaden participation in the AI ecosystem. This should not be interpreted as an assumption that the presence of women automatically produces gender-responsive technologies or policies. Representation alone does not guarantee influence or eliminate discrimination. It does, however, form part of a governance environment in which women have greater opportunities to participate in

decisions about technologies that increasingly affect their working and economic lives. UNESCO similarly places women's participation and leadership alongside measures addressing bias, stereotyping and discrimination within its approach to gender-responsive AI governance (UNESCO, n.d.).

AI may also create opportunities within the workplace itself. The ILO notes that, when responsibly designed and implemented, GenAI can improve working conditions, enhance productivity and support work-life balance. These outcomes are not predetermined. The same technologies can alter job quality, autonomy and working conditions in less favourable ways. Policy choices, social dialogue, women's representation in AI-related roles and measures addressing occupational segregation therefore influence whether technological change contributes to greater equality or reinforces existing gaps (ILO, 2026).

Describing AI as a potential tool for gender equality therefore requires caution. Technology alone cannot correct structural inequalities that precede it. Its contribution depends on the social, educational, labour-market and governance conditions within which it develops. Those conditions also vary across countries and among different groups of women, making a single pathway towards gender equality unrealistic. A gender-responsive approach needs both protection against discriminatory outcomes and efforts to expand meaningful opportunities for girls and women to participate in technological change.

The potential contribution of AI to gender equality is consequently both protective and enabling. Governance should seek to prevent AI systems from reproducing existing discrimination, but this is only part of the task. It should also help create conditions in which women can access education, employment and professional opportunities connected to technological change on more equal terms. In relation to women's economic independence, the relevant question is not whether every woman enters the AI sector, but whether the transformation associated with AI expands rather than narrows women's choices and opportunities to participate in economic life.

1.8 Research Gap

Research on artificial intelligence and gender has expanded considerably in recent years. Existing scholarship and policy research have examined women's representation in AI-related fields, gender differences in exposure to technological change, unequal access to digital and AI-related opportunities, algorithmic discrimination, and the implications of AI for employment and working conditions. Research on AI governance has also increasingly considered questions of gender, participation, power and structural inequality (Attard-Frost,

2025; Karagianni, 2025; UNESCO, n.d.). The relationship between AI and gender should therefore not be treated as an unexplored area of research.

An important concern emerging from this literature is that AI is being introduced into labour markets and societies in which gender inequalities already exist. Women and men do not necessarily enter AI-driven economic transformation from equivalent positions. Occupational segregation, differences in access to technological opportunities and the underrepresentation of women in AI-related employment can affect both exposure to technological change and access to its potential benefits. Recent ILO research, for example, finds that female-dominated occupations are more exposed to generative AI than male-dominated occupations, while women remain underrepresented in AI-related jobs. The same research emphasises that the effects of technological change are not predetermined and that policy choices will influence whether these developments support or undermine progress towards gender equality (ILO, 2026).

This raises a governance question that extends beyond the technical performance of individual AI systems. If AI develops within already unequal social and economic conditions, governance must determine how associated risks and opportunities are identified and addressed. Formally gender-neutral rules or policies may have different effects where the groups affected occupy different positions in the labour market and have unequal access to resources and opportunities. Gender-responsive AI governance has therefore increasingly been discussed in relation to structural gender gaps, participation in AI development and governance, and the prevention of discrimination and exclusion (UNESCO, n.d.). Feminist approaches to AI governance similarly draw attention to questions of participation and power, while feminist analysis of the EU AI Act has questioned whether formal approaches to non-discrimination are sufficient to address deeper structural inequalities (Attard-Frost, 2025; Karagianni, 2025).

At the same time, these governance debates are not always connected explicitly to women’s economic independence. Research on AI and work often focuses on occupational exposure, automation, augmentation, skills or job transformation, while studies of algorithmic discrimination frequently examine particular processes such as recruitment and workplace decision-making. Research on women’s economic empowerment, by contrast, demonstrates that employment alone does not necessarily provide economic autonomy: access to resources and opportunities, economic security and the capacity to make economic decisions are also important (Robbenhaar et al., 2026). These strands of research address related aspects of

gender inequality, but examining them together can provide a more specific understanding of what AI-driven transformation may mean for women's economic position.

The research gap addressed by this study should therefore be understood as a need for greater integration rather than an absence of previous research. In particular, there is scope to examine more closely how AI governance interacts with pre-existing gender inequalities in the world of work and how the governance of AI-related risks and opportunities may affect women's economic independence. This requires attention not only to potential harms, such as discriminatory outcomes or unequal exposure to labour-market disruption, but also to whether women have equitable opportunities to benefit from technological change.

This study addresses this gap by placing AI governance at the centre of the analysis and using women's economic independence as a key evaluative lens within the broader concept of women's economic empowerment. It examines how governance choices may respond to gendered differences in labour-market position, access to technological opportunities, representation and algorithmic decision-making, and considers their possible implications for women's economic security, autonomy and participation in economic life. The study does not assume that AI governance necessarily reinforces existing inequality, nor that greater representation of women automatically produces gender-equal outcomes. Instead, it investigates the conditions under which governance may mitigate existing inequalities, avoid reproducing them through technological transformation, and enable women to benefit more equitably from emerging economic opportunities.

1.9 Theoretical Framework

The relationship between AI governance, women's economic independence and gender equality cannot be adequately examined through a single theoretical perspective. The issues discussed in this chapter involve economic power, technological development, skills and education, labour-market structures, and differences among women themselves. This study therefore adopts a multidisciplinary theoretical framework combining Feminist Political Economy, Feminist Technology Studies, Human Capital Theory, Labour Market Segmentation Theory and Intersectionality. These perspectives are not treated as interchangeable theories. Rather, each provides a different analytical lens through which a particular dimension of the research problem can be examined. Together, they make it possible to consider both individual access to opportunities and the wider social and institutional conditions within which those opportunities are created and distributed.

Feminist Political Economy

Feminist Political Economy provides the first lens for examining the relationship between technological change and women's economic independence. Feminist political economy challenges gender-blind approaches to economic life by drawing attention to the power relations and hierarchies connecting markets, households, paid work, unpaid work and social reproduction. Care and other forms of reproductive labour are essential to economic and social life, yet they have historically been undervalued or made less visible in conventional economic analysis (Cantillon et al., 2023).

This perspective is particularly relevant to the distinction made in this study between employment and economic independence. Participation in paid work does not necessarily imply equal economic power, security or autonomy. Women's economic position can also be shaped by the conditions of employment, access to resources, and the distribution of paid and unpaid responsibilities. Feminist Political Economy therefore provides a framework for examining how AI-driven changes in work interact with economic structures that are already gendered.

The framework does not predetermine that women will benefit less from AI than men. Instead, it directs attention to the unequal economic conditions within which technological change occurs and asks whether those conditions influence the distribution of its risks and opportunities. In this study, it is therefore used to assess how AI governance may interact with existing patterns of economic power and with the conditions that support or constrain women's economic independence.

Feminist Technology Studies

Feminist Technology Studies provides a second perspective by examining the relationship between gender, society and technology. Rather than treating technology as inherently neutral or inherently oppressive to women, feminist technology scholarship emphasises that technologies are socially shaped and that gender and technology can be co-produced. Faulkner (2001), for example, argues that feminist technology studies avoids both overly optimistic accounts of technology as neutral and overly deterministic accounts of technology as necessarily harmful, focusing instead on the social processes through which technology becomes gendered. Wajcman (2004) similarly places technological development within wider gendered relations of power rather than treating technological change itself as the source of emancipation or inequality.

This perspective is central to the approach taken in this thesis. AI is not treated as an autonomous actor with gendered intentions. AI systems are developed, implemented and governed within social and institutional environments. Feminist Technology Studies therefore makes it possible to ask how gender norms, patterns of participation and distributions of technological expertise may interact with AI development and governance.

It also provides a way of examining women's participation in technological fields without assuming that women should choose particular occupations or that gender differences in occupational choices are inherently problematic. The analytical question is how such patterns emerge and whether stereotypes, educational opportunities, social expectations and institutional conditions contribute to shaping them. Equal opportunity does not require identical occupational choices; it requires attention to whether systematic barriers affect the choices and opportunities available to women and men.

Applied to AI governance, this framework shifts the question from whether AI itself is gendered to how AI is developed and governed within gendered social structures. It also allows the study to examine participation and whose experiences and perspectives enter technological decision-making, without assuming that women's representation automatically produces gender-equal outcomes.

Human Capital Theory

Human Capital Theory offers a different perspective. Becker (1964) conceptualises education and training as investments in human capital that can affect productivity, earnings and employment outcomes. The theory therefore provides a useful basis for analysing the importance of education, training and skills in enabling individuals to participate in changing labour markets.

This perspective is relevant to AI-driven transformation because access to digital and AI-related skills may affect workers' capacity to adapt to changing tasks and to benefit from emerging employment opportunities. From this perspective, unequal access to education and training can contribute to differences in the ability of individuals to respond to technological change.

Human Capital Theory is not, however, sufficient on its own for the purposes of this study. Differences in employment outcomes cannot necessarily be explained solely through individual qualifications, education or skills. Research on occupational sex segregation identifies a wider range of influences, including employer practices, discrimination, gender-role socialisation and opportunity structures (Reskin, 1993). Consequently, this study uses

Human Capital Theory to recognise the importance of skills and education while avoiding the assumption that responsibility for adapting to AI-driven change rests entirely with individual women. It is therefore considered alongside perspectives that address institutional and structural constraints.

Labour Market Segmentation Theory

Labour Market Segmentation Theory complements Human Capital Theory by shifting attention from individual characteristics to the organisation of labour markets. Segmentation approaches challenge the assumption of a single labour market in which all workers compete under equivalent conditions. Labour markets may instead be divided into segments characterised by different levels of pay, security, protection, mobility and opportunity. The International Labour Organization describes labour-market segmentation as the division of labour markets into separate sub-markets distinguished by different characteristics and rules, including divisions associated with contractual status, formality and categories of workers (International Labour Organization, n.d.).

This perspective is particularly relevant to gender because women and men are not evenly distributed across occupations and labour-market positions. Occupational sex segregation remains an important mechanism of labour-market inequality, and its persistence cannot be explained by a single factor. Reskin (1993) identifies both supply-side and demand-side explanations, including human-capital factors, gender-role socialisation, employer preferences, discrimination and personnel practices.

For this study, Labour Market Segmentation Theory helps explain why the same technological transformation may not have identical consequences for all workers. If women and men are concentrated in different occupations or forms of employment, differences in exposure to AI, opportunities for augmentation, access to emerging jobs and vulnerability to changes in working conditions may partly reflect their existing labour-market positions. This framework therefore connects AI-driven transformation to the structural organisation of employment rather than attributing differences in outcomes exclusively to individual choices or skills.

Intersectionality

The final analytical perspective is Intersectionality. Crenshaw (1989) developed the concept in response to approaches that treated race and gender as mutually exclusive categories and therefore failed to capture experiences located at their intersection.

Intersectionality challenges single-axis analysis and draws attention to the limitations of explaining inequality through one social category alone.

This perspective is necessary because the category ‘women’ does not describe a homogeneous economic or social group. Gender can intersect with class, race or ethnicity, migration status, education, geographical location and other dimensions of social position. Women living in different countries and social environments may therefore have very different access to technological education, employment, economic resources and AI-related opportunities.

Intersectionality prevents this study from assuming that the effects of AI-driven transformation can be understood through gender alone. It also has implications for AI governance: measures intended to promote gender equality may not affect all women in the same way when their economic and social positions differ. The framework is therefore used to interpret variation within women’s experiences rather than treating gender as a single and sufficient explanation for technological or economic inequality.

Conceptual Framework of the Study

Taken together, these five perspectives provide the conceptual framework through which this study examines AI governance, women’s economic independence and gender equality. They are assigned distinct analytical tasks rather than presented as a list of background theories. Feminist Political Economy connects technological change to paid and unpaid work, resources and bargaining power. Feminist Technology Studies directs attention to the organisational choices and social assumptions through which AI systems are designed and used. Human Capital Theory identifies the role of education and skills, while its limits prevent unequal outcomes from being reduced to individual deficits. Labour Market Segmentation Theory explains how occupational position, job quality and contractual status structure exposure to risk and access to benefit. Intersectionality tests whether claims framed around women as a group remain valid across differences in class, race or ethnicity, migration status, disability, age and location.

These functions are carried forward in the analysis. Chapter 2 uses Feminist Technology Studies when examining design objectives, data and organisational deployment; Human Capital Theory and its critique when assessing skills and adaptation; and Labour Market Segmentation Theory when interpreting occupational exposure, job quality and the distribution of economic gains. Chapter 3 then combines the structural concerns of Feminist Political Economy with these lenses to evaluate institutional responsibility, while

intersectionality informs the choice of comparison groups and the limits of aggregate gender measures. Their value is therefore assessed through the questions they enable the thesis to ask, not through an assumption that any one theory predicts the outcome.

The conceptual framework does not assume a predetermined causal relationship between the gender composition of technology or AI governance and negative outcomes for women. Nor does it assume that AI will necessarily increase or reduce gender inequality. Instead, it treats AI as a technological transformation occurring within existing social, economic and institutional structures. The central analytical concern is whether AI governance recognises these pre-existing inequalities and how governance choices shape women's exposure to the risks and opportunities associated with technological change.

Within this framework, women's economic independence serves as a key evaluative lens. The analysis therefore extends beyond whether AI creates or removes jobs and considers whether AI-driven changes affect women's access to secure employment, economic opportunities, skills and resources, as well as their capacity to make autonomous economic choices. Gender equality represents the broader context within which these outcomes are assessed.

The framework can consequently be understood through the relationship between three central elements: the governance of AI, the gendered social and economic conditions within which AI is introduced, and the economic outcomes experienced by women. The five theoretical perspectives provide complementary tools for examining the mechanisms connecting these elements. This allows the study to investigate, rather than presume, whether and under what conditions AI governance can avoid reproducing existing inequalities through technological change and support more equitable opportunities for women to benefit from an increasingly AI-influenced economy.

Chapter 2

AI Governance, Gender Equality, and Women's Economic Independence

This chapter maps the evidentiary and institutional landscape within which AI governance operates, including patterns of representation, employment opportunity, job displacement, access to skills, algorithmic bias, financial security and existing policy frameworks. Each section establishes what the available empirical research and legal or policy materials show about women’s position in relation to a specific dimension of AI-driven change. Chapter 3 builds on this mapping by examining the distribution of power and institutional responsibility and by evaluating whether existing governance arrangements respond adequately to the patterns identified here. It draws on illustrative regulatory decisions and implementation evidence to test broader governance claims. The distinction between the two chapters is therefore one of function rather than importance: Chapter 2 establishes what the available evidence shows, while Chapter 3 asks what those findings mean for power, responsibility and the adequacy of governance responses.

2.1 Gender Representation in AI Development and Governance

The rapid expansion of artificial intelligence has created new forms of economic and technological influence, and raised questions about who participates in the development and governance of these technologies. Women remain underrepresented in several important areas of the AI ecosystem, although the extent of this underrepresentation varies considerably across occupations, levels of seniority and types of AI-related activity. Recent evidence therefore suggests that gender representation in AI cannot be adequately understood through a single measure of women's overall participation. It is also necessary to examine where women are positioned within the AI ecosystem and the extent to which they have access to roles associated with technological development, leadership and decision-making.

Recent data make this uneven distribution visible. The World Economic Forum (2026), drawing on LinkedIn data, reports that women account for 36.6 per cent of individual contributors in AI firms, but their representation declines to 25.3 per cent at the highest levels of management. Differences are also visible across particular AI occupations. Across 19 economies for which comparable data are available, women represent an average of 44.8 per cent of data annotators, compared with 19.3 per cent of AI engineers and 20.6 per cent of machine-learning engineers. These estimates do not include China, which is an important limitation given the country's significant role in the global AI ecosystem. Nevertheless, the differences indicate that women's participation is not evenly distributed across the AI value chain. Numerical participation in AI, therefore, does not by itself reveal how women are

positioned across different technical, organisational and leadership roles within the AI ecosystem.

These patterns form part of a broader pathway through which individuals enter, remain in and progress within AI-related fields. Women's representation at senior levels cannot be separated entirely from earlier stages involving education, skills acquisition, recruitment, retention and professional advancement. The OECD (2024), for example, identifies several factors that may contribute to gender divides in technology, including gender stereotyping from an early age, a lack of role models in STEM, discrimination in recruitment and unfavourable working conditions in technology-related sectors. Similarly, UNESCO's regional study of AI and gender in South Asia examines women's participation across the AI ecosystem, from education and research to employment, entrepreneurship and leadership, and identifies barriers that can accumulate along this pathway (UNESCO, 2026). As the latter evidence concerns six South Asian countries, it should not be treated as representative of women's experiences globally. It nevertheless illustrates why gender representation at the highest levels of AI cannot be examined only at the point at which leadership positions are allocated.

From this perspective, underrepresentation should not automatically be interpreted as evidence that every numerical difference results from discrimination, nor should numerical parity be treated as sufficient evidence of substantive equality. The more relevant question is whether women have substantively equitable opportunities to acquire AI-related expertise, enter relevant professions, progress within organisations and participate in positions of leadership and governance. This distinction is particularly important because the absence of an explicit formal barrier does not necessarily establish that the conditions under which women and men enter and progress through these pathways are equivalent.

AI governance brings a further distinction into view between numerical presence and meaningful participation. A governance body may include women without necessarily providing all participants with equivalent influence over agendas, priorities or final decisions. Conversely, the gender composition of a decision-making body alone does not determine whether its policies will adequately respond to gendered risks and opportunities. UNESCO's Women4Ethical AI initiative is informative in this respect because it identifies the advancement of women's participation and leadership in AI and the promotion of gender-responsive AI governance as related but distinct objectives (UNESCO, n.d.). The implication is that representation, participation and policy outcomes should not be treated as interchangeable measures of gender equality in AI governance.

Importantly, the case for women's participation should not depend on an assumption that women entering AI leadership or governance necessarily represent a single set of 'women's interests'. Women are not a homogeneous social group, and their experiences of technology and economic life may differ according to factors including socioeconomic position, education, geography, race, ethnicity, migration status and other intersecting conditions. Nor can the presence of women in decision-making positions be assumed automatically to produce gender-responsive policies. Rather, patterns of representation raise a broader question of whether women have equitable access to the pathways through which technological expertise, leadership and decision-making power are acquired.

The same issue arises in participatory approaches to AI governance. An integrative review of 30 studies on social participation in AI governance found that participation can contribute to identifying inequalities, improving transparency and addressing forms of algorithmic bias in public-sector AI governance, while also finding that the practical implementation of participation remains limited and that perspectives from the Global North continue to dominate much of the relevant guidance (De Carvalho et al., 2026). Such findings do not establish that increasing the numerical representation of women will automatically improve AI governance. They do, however, reinforce the importance of considering who is able to participate meaningfully in governance processes and whose knowledge and experiences are incorporated into decisions about AI.

The relationship between representation and gender-responsive governance is therefore better treated as an open empirical and analytical question than as a predetermined conclusion. Greater numerical representation may expand access to positions of technological and institutional power, but its consequences depend on the conditions under which participation occurs and the extent to which participants can exercise meaningful influence. Equally, the existence of apparently gender-responsive policies does not make questions of representation irrelevant, since unequal access to leadership and decision-making positions constitutes a separate concern regarding participation in technological governance.

For the purposes of this study, women's representation in AI is therefore examined at three analytically distinct levels: numerical presence, meaningful participation and decision-making power. These dimensions are subsequently considered alongside, rather than equated with, gender-responsive governance outcomes. This approach makes it possible to investigate whether and under what conditions women's participation in AI development and governance is associated with changes in technological and policy decision-making, without assuming in

advance either that representation is irrelevant or that numerical parity alone is sufficient to produce gender-equal outcomes.

2.2 Power and Decision-Making in AI Policy and Technological Design

Power in AI governance extends beyond the numerical representation of women examined in the previous section. Representation concerns who gains access to spaces of technological development, leadership and governance, whereas power also concerns how decisions within those spaces are made, which considerations shape them, and how responsibility for their consequences is allocated. Decisions affecting the development and use of AI occur across the AI lifecycle and involve a range of actors, including policymakers, regulators, technology companies, developers, managers and organisations deploying AI systems. Consequently, analysing gendered power in AI governance requires attention not only to who participates in decision-making, but also to the processes and assumptions through which technological and policy choices are made.

Technical design is itself an important site of decision-making. The NIST Artificial Intelligence Risk Management Framework recognises that decisions made during the design, development, deployment, evaluation and use of AI systems can reflect both human cognitive and systemic biases (NIST, 2023). Choices concerning the purpose of an AI system, the data on which it relies, the assumptions embedded in its design and the conditions under which it is deployed may therefore have consequences extending beyond technical performance. This does not imply that every technical choice is inherently discriminatory. Rather, it demonstrates that technological design involves human judgement and that decisions made at different stages of the AI lifecycle can influence how risks and benefits are subsequently distributed. This analysis operationalises the Feminist Technology Studies lens developed in Section 1.9: technical outputs are examined as products of social and organisational choices rather than as autonomous effects of technology.

The issue becomes especially important when AI systems operate within social and economic environments already characterised by gender inequalities. Historical data, for example, may reflect patterns produced under earlier conditions of inequality. The United Nations Economic Commission for Europe (UNECE, 2025) notes that AI systems can inherit or amplify gender biases embedded in historical data, design decisions and previous implementations, with potential implications for women's economic participation and access to services and opportunities. The presence of historical data does not mean that an AI system

will necessarily produce discriminatory outcomes. What it does create is a governance question: whether relevant risks have been identified, assessed and addressed during the development and deployment of the system.

This becomes especially important when considering apparently gender-neutral approaches to AI. Applying identical criteria to women and men does not necessarily establish that the conditions under which those criteria operate are equivalent. Where pre-existing gender inequalities affect employment patterns, occupational positions, access to resources or caring responsibilities, a decision-making process that does not consider these conditions may fail to identify differentiated effects. UNESCO's Recommendation on the Ethics of Artificial Intelligence reflects this concern by calling for a transversal gender perspective in Ethical Impact Assessment and for gender stereotyping and discriminatory biases to be identified and proactively addressed throughout the AI system lifecycle (UNESCO, 2021). Gender responsiveness in AI governance therefore involves more than the absence of explicit gender differentiation; it also requires consideration of whether apparently neutral technological choices interact with existing inequalities.

These governance questions become especially relevant in the changing world of work. As discussed in Chapter 1, AI-driven transformation takes place within labour markets already characterised by gendered occupational patterns and unequal conditions. Governance decisions concerning the adoption and use of AI therefore do not operate in a socially neutral environment. Their implications depend partly on the economic and occupational structures within which AI systems are introduced, making attention to existing inequalities an important element of gender-responsive decision-making.

Power is also exercised through organisational decisions about how AI is used. Algorithmic systems can perform or support managerial functions such as organising, assigning, monitoring and evaluating work (ILO, n.d.). Their introduction therefore raises governance questions concerning who determines the criteria on which these systems operate, how their effects are assessed and where responsibility remains when consequential decisions are supported by automated systems. Detailed questions concerning algorithmic decision-making in recruitment, promotion and workplace practices are examined separately in Section 2.6.

Transparency matters here. A favourable outcome at one point in time does not, by itself, show that an AI-assisted decision-making process is adequately governed. Where individuals affected by consequential decisions have little information about the basis on which an AI

system is being used, scrutiny of the process and identification of problems may become more difficult. Transparency should therefore be considered alongside evaluation, oversight and accountability. UNESCO's Ethical Impact Assessment provides one example of this broader approach by encouraging the assessment of potential positive and negative impacts, engagement with relevant stakeholders and the development of measures to mitigate adverse outcomes (UNESCO, n.d.).

Yet transparency on its own is not sufficient. Providing information about an AI system does not necessarily ensure that harmful decisions can be challenged or that responsibility for them is clearly allocated. The NIST AI Risk Management Framework similarly emphasises the importance of clearly defined roles and responsibilities in human-AI configurations (NIST, 2023). From a governance perspective, the relevant issue is therefore not simply whether information about a system is available, but whether mechanisms exist to assess its effects, oversee its operation and establish responsibility for consequential decisions.

Participation also requires careful treatment. Evidence from workplace settings shows that social dialogue has enabled worker representatives in some contexts to influence decisions concerning AI adoption, algorithmic management and working conditions (Doellgast et al., 2025). However, this does not imply that every worker must participate directly in every organisational decision concerning AI. Organisations necessarily allocate decision-making authority to particular actors. The governance question concerns the basis on which that authority is exercised, which interests and potential impacts are considered, and what mechanisms exist for scrutiny and accountability.

The evidence reviewed in this section identifies four locations at which power can shape AI outcomes: problem definition, the selection of criteria and data, the prioritisation of risks, and decisions about implementation and evaluation. Identifying these locations does not establish that women decision-makers necessarily make different or more gender-equitable choices than men. It shows where formal authority and agenda-setting capacity can affect which social conditions become visible to governance and which remain outside it. Chapter 3 uses these decision points to examine how responsibility is exercised, contested and made accountable.

2.3 AI and Women’s Employment Opportunities

The transformation of work through Artificial Intelligence creates potential employment opportunities as well as risks. For women, however, the existence of new technological

possibilities does not necessarily mean that these possibilities are equally accessible or economically meaningful. In this study, employment opportunity is considered at several interconnected levels: the creation of new or transformed forms of work, women's ability to access these opportunities, their capacity to make effective use of AI within existing employment, and the extent to which such opportunities can contribute to economic security and independence. The reason is straightforward: technological opportunity alone does not determine who ultimately benefits from technological change.

AI-related employment opportunities can emerge both within the AI sector and through the transformation of work outside it. The first category includes occupations directly involved in developing, maintaining and supporting AI systems. OECD evidence indicates that the AI workforce, defined narrowly as workers with the skills to develop and maintain AI systems, accounts for just above 0.3 per cent of employment across OECD countries and is concentrated among men and university-educated workers. The OECD also notes that many ICT- and AI-related jobs are relatively lucrative, meaning that unequal access to them may have implications not only for occupational representation but also for women's access to higher-value economic opportunities (OECD, 2024a). Its significance for gender equality depends partly on whether women can enter and progress within areas of the AI economy in which economic rewards and career opportunities are concentrated.

Recent evidence also shows why the type of opportunity matters. LinkedIn data reported in the World Economic Forum's Global Gender Gap Report 2026 show substantial differences in women's representation across AI occupations. Across 19 economies with comparable data, women account on average for 44.8 per cent of data annotators, compared with 19.3 per cent of AI engineers and 20.6 per cent of machine-learning engineers (World Economic Forum, 2026). These estimates do not include China and cover a selected set of occupations with sufficient data for cross-country comparison. They should therefore not be interpreted as a complete picture of women's participation in the global AI economy. Nevertheless, they illustrate that participation is unevenly distributed across different forms of AI-related work. In the United States, the same report finds that data annotation, the AI role in which women are most represented, is also among the lowest-paid AI roles, while women are less represented in many of the highest-paid AI occupations. Employment in the AI economy cannot therefore be evaluated simply by counting the number of opportunities available to women; the quality, remuneration and prospects for progression associated with those opportunities are also relevant to their potential contribution to economic independence.

A second, broader form of opportunity may affect a much larger group of women: the use of AI within existing occupations. Generative AI can assist with particular tasks, reduce the time required for some activities and, under certain conditions, increase worker productivity. A recent ILO review of experiments, firm-level evidence, platform studies and worker surveys finds that productivity gains from generative AI are observable, although they are uneven and, in some settings, remain difficult to verify outside experimental conditions (Merola et al., 2026). In other words, AI may create economic opportunities without necessarily creating an entirely new occupation. Workers may instead benefit through changes in how existing work is performed, the range of tasks they can undertake or the productivity with which those tasks can be completed.

Productivity gains, however, should not automatically be equated with improvements in women's economic position. The same ILO review finds that worker-reported time savings have not yet clearly translated into higher measured output, earnings or employment (Merola et al., 2026). It would therefore be premature to assume a direct progression from AI use to higher productivity, from productivity to higher income, and ultimately from higher income to greater economic independence. Here, AI-enabled productivity is better understood as a potential economic opportunity whose eventual value depends on how productivity gains are distributed and whether workers are able to convert them into improvements in employment quality, earnings, security or career development.

Access to these potential benefits is uneven as well. OECD evidence indicates that women may have less access not only to AI-related occupations but also to productivity-enhancing AI tools in the workplace. A Danish study discussed by the OECD found that female workers were 20 percentage points less likely than male workers in the same occupation to report having used ChatGPT (OECD, 2024a). Because the finding concerns one technology in one national study, it should not be generalised to all forms of AI use. It does, however, illustrate an important distinction between the availability of a technology and its effective adoption. If productivity-enhancing tools are available but women use or access them less frequently, technological progress alone cannot ensure an equal distribution of its potential employment benefits.

National and economic context also shapes these opportunities. Evidence covering 135 countries shows that the potential labour-market effects of generative AI are not distributed uniformly between advanced and developing economies. Gmyrek et al. (2026) find that developing economies generally face lower aggregate automation exposure than advanced economies but comparable potential for task augmentation. At the same time, gaps in digital

infrastructure can limit the ability of workers in developing economies to realise potential productivity gains. The authors therefore warn that some developing economies may experience disruption before the benefits associated with generative AI are fully realised. The evidence therefore shows that an employment opportunity identified on the basis of technological capability may not constitute an effective opportunity where the infrastructure required to access that technology is absent.

Gender intersects with these contextual differences as well. Women do not constitute a homogeneous group with equal access to AI-related opportunities. Geography, education, socioeconomic position, occupation, migration status and access to digital infrastructure can influence the extent to which individual women are able to benefit from technological change. Claims that AI creates employment opportunities “for women” require attention to which women, in which labour markets and under what conditions. A technological opportunity that is accessible to a highly educated professional in a digitally connected labour market may have limited relevance for a woman working in an informal or poorly connected economic environment.

These differences bring AI governance back into the analysis. Governance cannot itself guarantee that technological change will strengthen women’s economic independence, but policy choices can influence the conditions under which opportunities become accessible. The OECD (2024a), for example, identifies inclusive access to upskilling and reskilling, attention to gender differences in AI adoption, and monitoring AI’s employment effects through a gender lens as relevant policy considerations. Similarly, evidence on developing economies indicates that digital infrastructure, education and skills systems, labour-market institutions and social protection influence whether potential augmentation and productivity benefits can be realised (Gmyrek et al., 2026). The discussion returns to these issues in greater detail in subsequent sections, particularly Section 2.5 on digital skills and access to future employment.

The evidence reviewed in this section supports a three-stage distinction between the creation of an opportunity, access to it and its conversion into an economically meaningful benefit. Research showing new forms of work or productivity gains establishes the first stage, while evidence on adoption, occupational segregation and working conditions bears on the second and third. Keeping these stages separate prevents the availability of AI-enabled work from being treated as evidence of improved economic independence. It also identifies the points at which the distribution of opportunity may diverge before Chapter 3 evaluates the institutional responsibility attached to those differences.

2.4 AI and the Risk of Job Displacement for Women

The growing capacity of Artificial Intelligence to perform tasks previously carried out by workers has raised concerns about possible job displacement. For women, this concern is particularly relevant because technological change is taking place within labour markets that are already characterised by gendered occupational patterns. Yet exposure to AI should not be treated as equivalent to automation, nor should automation potential be interpreted as evidence of actual job loss. The ILO's refined global index measures the potential exposure of occupations to Generative AI rather than observed employment displacement. Globally, one in four workers is employed in an occupation with some degree of GenAI exposure, but because most occupations continue to include tasks requiring human input, job transformation is considered more likely than complete replacement (Gmyrek et al., 2025). Distinguishing between exposure, the automation of particular tasks, transformation of a job and actual displacement is therefore essential when assessing the implications of AI for women's employment.

Women nevertheless show a distinctive pattern of exposure. At the global level, 4.7 per cent of female employment falls within the highest category of GenAI exposure, compared with 2.4 per cent of male employment. The difference becomes considerably larger in high-income countries, where the corresponding shares are 9.6 per cent and 3.5 per cent (Gmyrek et al., 2025). These figures are not estimates of the proportion of women and men who will lose their jobs. Instead, they show that women and men are differently positioned across occupations that may be affected by technological change. Higher exposure should therefore be understood as an indication of potential transformation rather than a prediction of unemployment.

Occupational segregation is important in explaining this difference. Evidence from ILO harmonised microdata covering 84 countries shows that female-dominated occupations are considerably more likely to be exposed to GenAI than male-dominated occupations. This pattern reflects, in part, women's concentration in clerical, administrative and business-support roles containing tasks with relatively high automation potential (ILO, 2026). Women's higher exposure cannot therefore be understood simply as a consequence of gender in isolation. It is connected to the existing distribution of women and men across occupations and tasks. AI enters a labour market in which employment is already gender-segregated, and technological change may consequently interact with inequalities that existed before the

technology was introduced. Labour Market Segmentation Theory is applied here to interpret that distribution: exposure and adaptive capacity vary because workers occupy labour-market segments with different security, mobility, training and progression opportunities.

Higher exposure, however, does not determine a single employment outcome. An occupation can change substantially without disappearing. Some tasks may be automated while workers continue to perform others, assume new responsibilities or use AI as part of their existing work. This distinction is particularly important when considering women's economic independence. A change in job content does not necessarily constitute an economic threat when workers remain employed and have an effective opportunity to acquire the skills required to adapt. Under these conditions, AI-driven change may represent a transformation in the nature of employment rather than displacement from employment.

The way this transition is managed therefore matters. Workers cannot necessarily be expected to respond to new technological requirements without appropriate opportunities to learn and adapt. The OECD identifies inclusive upskilling and reskilling as an important element of a fair AI transition, both to enable workers to work with AI and adapt to changes within their jobs, and to support movement from declining occupations and sectors into new and growing ones (OECD, 2024a). The ILO similarly emphasises the importance of managing AI-related transitions through social dialogue and targeted policy responses (Gmyrek et al., 2025). The mere existence of training, however, should not automatically be treated as evidence that workers are adequately protected. What matters is whether they have a realistic and accessible opportunity to acquire the required skills and use them to remain in employment or move into viable alternative work.

This question has particular relevance for women because the ability to adapt is not distributed equally among workers. As discussed in earlier sections, women's labour-market positions differ according to occupation, education, socioeconomic circumstances, access to technology and other intersecting conditions. A worker who has access to employer-supported training and a viable pathway into transformed work is in a different position from a worker whose tasks are automated without comparable support or realistic alternative employment. The risk associated with AI therefore lies not only in whether particular tasks can technically be automated, but also in the conditions under which workers are expected to adjust to changing job requirements. The question of unequal access to digital skills and future employment is examined more fully in Section 2.5.

National context also shapes the pattern of exposure. The ILO estimates that 34 per cent of employment in high-income countries falls within one of the GenAI exposure gradients, compared with 11 per cent in low-income countries (Gmyrek et al., 2025). This does not mean that workers in lower-income economies are necessarily better protected from technological disruption. The index measures potential exposure under existing occupational structures, while actual adoption and employment effects depend on the circumstances in which AI is introduced. Lower measured exposure should therefore not be interpreted as equivalent to lower labour-market vulnerability. Differences in economic structure, technological adoption and institutional capacity can shape both the pace of transformation and workers' ability to respond to it.

From the perspective of women's economic independence, displacement becomes especially significant when technological change leads to loss of employment, declining earnings, prolonged exclusion from work or movement into less secure employment. Such outcomes can reduce a woman's capacity to meet her own economic needs and may increase economic dependence on household members, family or public support. These consequences, however, should not be assumed to follow automatically from AI exposure. Their severity depends on whether displacement actually occurs, whether alternative employment is available and accessible, the quality of that employment, and the resources available to workers during the transition. The same technological change may therefore have very different economic consequences for different women.

This is where AI governance becomes central to the analysis. Gender-responsive governance does not require preventing firms from adopting productivity-enhancing technologies or from changing the organisation of work. Nor can governance eliminate every form of disruption associated with technological change. The relevant question is how the transition is managed and how its costs and benefits are distributed. Monitoring employment effects through a gender lens, providing inclusive and accessible opportunities for upskilling and reskilling, facilitating transitions between occupations, and strengthening social dialogue can influence whether AI-related transformation results in adaptation or exclusion. The OECD specifically recommends gender-sensitive monitoring and inclusive approaches to reskilling, while the ILO stresses the importance of policy choices and social dialogue in shaping how GenAI affects working conditions and gender equality (OECD, 2024a; International Labour Organization, 2026).

The available evidence supports conclusions about occupational exposure and the potential transformation of tasks, but it does not yet establish the scale of actual employment

displacement. The transition proceeds through several stages: exposure may lead to task redesign; organisational choices determine whether redesigned tasks complement or replace workers; and access to training or occupational mobility affects the resulting employment outcome. Women's concentration in more highly exposed occupations therefore identifies a transition risk rather than a prediction of widespread female job loss. Evidence on adaptation and mobility is required to determine whether that risk becomes unemployment, declining earnings or greater insecurity.

2.5 AI, Digital Skills, and Access to Future Employment

As AI becomes more deeply integrated into the workplace, access to future employment will increasingly depend not only on whether jobs remain available, but also on whether workers can acquire and use the skills required in changing forms of work. These skills extend beyond the technical expertise needed to develop AI systems. Recent evidence indicates growing demand for a combination of digital and AI literacy, higher-order cognitive abilities, adaptability and socioemotional skills as AI changes the way tasks are performed across occupations. AI literacy, in particular, is increasingly being treated as a foundational capability for workers operating in AI-augmented environments (Bardak et al., 2026). For women, the relevant question is therefore not simply whether they possess specialised technical skills, but whether they have effective access to the broader capabilities increasingly required to enter, remain in and progress within changing labour markets.

This distinction is important because unequal use of AI technologies has already been observed even where the technologies themselves are broadly available. Using data from the United States Survey of Consumer Expectations, Aldasoro et al. (2024) find that 50 per cent of men reported using generative AI, compared with 37 per cent of women. Differences in demographic characteristics, privacy concerns and perceptions of the risks and opportunities associated with AI explain only part of this gap, while self-assessed knowledge of generative AI emerges as the most important explanatory factor. These findings do not establish that women have inherently lower technological ability. Rather, they suggest that differences in knowledge, familiarity and engagement with emerging technologies can influence who is positioned to make use of them.

Evidence from professional settings provides further support for distinguishing access to technology from the ability to use it effectively. Chugunova et al. (2026), drawing on a survey of more than 6,000 researchers in two major German research organisations, identify a gender

gap in both familiarity with AI tools and their frequency of use. AI familiarity accounts for most of the observed gap in their analysis. Importantly, the study does not find evidence that women are simply more sceptical about AI or perceive it as less useful. Among researchers who had developed familiarity with AI and engaged with relevant learning resources, women reported rates of AI use similar to, and in some cases higher than, those of men. Lack of knowledge was also the most frequently reported barrier among female respondents. Although this evidence comes from a highly educated and specialised population and cannot be generalised to women across the labour market, it demonstrates that gender differences in AI adoption can persist even among workers with high levels of education.

Differences in the effective use of AI can have consequences beyond technology adoption itself. Evidence from academia, for example, indicates that the productivity effects associated with generative AI may not be evenly distributed. Tang et al. (2025) find that, following the emergence of ChatGPT, the increase in research productivity among male researchers in their study was 6.4 per cent greater than among female researchers. Survey evidence accompanying the analysis also found more frequent use of generative AI among male researchers. These results relate to a specific occupational environment and should not be treated as evidence of a universal gender effect. They nevertheless illustrate a broader concern: where access, familiarity or use differs between groups, the economic benefits associated with a productivity-enhancing technology may also be distributed unevenly.

For this reason, the availability of training should be distinguished from effective access to training. An organisation may formally provide the same learning opportunity to all workers while differences in timing, cost, workload, digital access or other circumstances affect workers' ability to participate. This distinction may be particularly relevant for women where unequal caring and household responsibilities create additional constraints on the time available for training and reskilling. Such responsibilities should not be assumed to affect all women in the same way, but they can shape whether a formally available learning opportunity is realistically accessible. OECD evidence on adult learning supports this concern: family commitments disproportionately affect women's participation in education and training, even where overall gender differences in participation are small (OECD, 2024c). Formal availability therefore does not necessarily establish substantive equality of opportunity. This does not mean that every difference in training participation should be attributed to discrimination, nor that employers can remove every external constraint affecting workers. It does mean, however, that where new AI-related skills become important for continued

employment or career progression, the accessibility of opportunities to acquire those skills becomes relevant to the governance of technological change.

This issue is particularly important when employers themselves introduce technologies that alter the skills required to perform a job. As discussed in Section 2.4, changes in tasks need not undermine economic independence where workers have a realistic opportunity to adapt. That opportunity becomes less meaningful, however, if the skills required for adaptation are formally identified but the means of acquiring them are inaccessible in practice. Training that exists but cannot realistically be used by affected workers may do little to protect their position in a changing workplace. Effective access therefore involves more than the presence of a course or learning resource; it also concerns whether workers can participate, acquire relevant capabilities and subsequently apply them in their work.

At the same time, preparing women for future employment should not be reduced to encouraging all women to enter programming, engineering or other highly technical AI occupations. The changing skills landscape is considerably broader. Evidence on AI and work indicates that technological adoption can increase the importance of general digital capabilities, AI literacy, critical thinking, problem-solving, adaptability and interpersonal skills alongside specialised technical expertise (Bardak et al., 2026). This broader understanding is especially important because AI is likely to affect workers across a wide range of occupations, including those who will never design or develop an AI system. Policies focused only on producing more AI specialists would therefore address only one part of the challenge.

The relationship between skills and future employment is also not linear. Acquiring a skill does not by itself guarantee access to employment, higher earnings or career progression. Labour-market demand, occupational structures, recruitment practices and the quality of available jobs continue to shape whether newly acquired capabilities can be converted into economic opportunities. The same qualification may therefore produce different outcomes for workers situated in different labour markets or socioeconomic circumstances. From the perspective of women's economic independence, skills should consequently be understood as an enabling condition rather than a guaranteed route to economic security.

These considerations also raise questions of AI governance. Decisions about technological adoption are closely connected to decisions about who is expected to acquire new capabilities, who receives institutional support to do so, and how the costs of adaptation are distributed between workers, employers and public institutions. Evidence from

professional organisations suggests that institutional learning environments themselves may matter: Chugunova et al. (2026) find that a continuous learning orientation is associated with both greater AI familiarity and adoption. This does not establish that organisational policy alone can eliminate gender differences, but it does indicate that AI adoption takes place within institutional environments that can facilitate or constrain learning.

A gender-responsive approach to skills policy should therefore avoid treating unequal preparedness for AI as simply an individual deficit to be corrected by women themselves. Where technological change alters the requirements of employment, governments, educational institutions and employers all influence the conditions under which workers can adapt. Their responsibilities differ, but decisions concerning education, lifelong learning, workplace training and technological implementation can affect who is able to acquire and use emerging skills. The objective is not to guarantee identical outcomes for every worker, but to ensure that apparently open opportunities do not become inaccessible in practice to groups already facing structural disadvantages.

The skills literature adds an adaptive-capacity stage to the employment pathway mapped in this chapter. Learning opportunities must exist, workers must be able to use them, acquired skills must be applicable in practice and labour markets must offer positions in which those skills have economic value. Similar overall participation in adult education can therefore coexist with unequal familiarity with a particular AI tool; the two measures capture different points in this sequence. Locating skills within this wider pathway also avoids treating occupational adaptation as an individual obligation detached from time, cost, care responsibilities and the availability of suitable work.

2.6 Algorithmic Bias in Recruitment, Promotion, and Workplace Decisions

The growing use of Artificial Intelligence in employment decision-making extends beyond recruitment. AI systems can be used to analyse applications, rank candidates, support performance evaluation, allocate tasks, monitor workers and contribute to decisions concerning promotion and other conditions of employment. These applications are particularly relevant to women’s economic independence because employment decisions do not only determine whether an individual obtains a job. They can also influence income, career progression, employment security and access to future economic opportunities. The governance of employment-related AI therefore raises questions about how algorithmic outputs are produced, interpreted and used within organisational decision-making.

As discussed in Section 1.5, algorithmic bias should not be understood as an independent intention of an AI system to discriminate. AI systems operate on the basis of objectives, data and criteria determined through human and organisational choices. Berg and Johnston (2025) identify the objective assigned to an AI system, the data on which it relies and the way in which it is programmed as important elements in understanding the use of AI in human resource management. In employment contexts, this distinction is particularly significant because historical data may accurately describe previous employment patterns while simultaneously reflecting the unequal conditions under which those patterns developed.

The fact that data are accurate does not necessarily mean that using them to make predictions about future workers will produce equitable outcomes. For example, historical organisational data may show that men have occupied a larger proportion of senior positions or have accumulated particular forms of managerial experience. Such information may accurately describe the organisation's past. However, it does not explain why these differences developed. Unequal access to education and training, occupational segregation, caring responsibilities, social expectations and unequal opportunities for career progression may all contribute to differences in the employment histories of women and men. Recent research on women in the digital economy similarly shows that educational disparities, occupational segregation, persistent pay gaps, caring responsibilities and algorithmic management can interact in ways that shape women's economic opportunities (Rani, Gobel, & Uludag, 2026).

This creates an important distinction between recognising differences in qualifications or experience and assuming that such differences emerged under equal conditions. If two candidates have genuinely different levels of relevant experience, gender equality does not require an employer to disregard those differences or automatically select a woman in order to achieve numerical equality. Equal opportunity should not be confused with equal outcomes. However, apparently objective differences between candidates may themselves have developed through unequal access to the opportunities through which qualifications, experience and professional networks are accumulated. From this perspective, the relevant question is not simply whether an algorithm applies identical criteria to women and men, but also whether the criteria and data on which it relies reflect structural inequalities that have shaped their previous opportunities.

This issue is particularly important because algorithmic systems can potentially transform past patterns into inputs for future decisions. Where historical employment patterns reflect unequal access to opportunities, systems trained on or evaluated against those patterns may

reproduce aspects of them when identifying suitable candidates or predicting future performance. This does not mean that historical data should automatically be considered discriminatory or that every difference in algorithmic outcomes demonstrates gender discrimination. Rather, persistent differences should provide a reason to examine how the system operates, which variables influence its outputs and whether apparently neutral criteria interact with existing inequalities.

The concern extends beyond recruitment. AI-supported systems may influence promotion, performance evaluation, task allocation, scheduling and workplace monitoring. Decisions in these areas can have cumulative economic effects. Access to desirable tasks can contribute to professional development; performance assessments can affect promotion and remuneration; and scheduling decisions can influence both earnings and the ability to reconcile paid work with caring responsibilities. Evidence from the platform economy illustrates how algorithmic management can interact with existing gender inequalities, including occupational segregation, unpaid care responsibilities and insecure income (Rani et al., 2026). Consequently, the effects of algorithmic management cannot always be assessed by examining a single decision in isolation.

The European Union Artificial Intelligence Act reflects the significance of these risks. Under Annex III of Regulation (EU) 2024/1689, specified AI systems intended for recruitment or selection, including systems used to analyse or filter applications and evaluate candidates, are classified as high-risk subject to the Act's classification rules. The same category covers specified systems used for decisions concerning work-related relationships, promotion or termination, task allocation based on individual behaviour or characteristics, and the monitoring or evaluation of workers. Recital 57 explicitly recognises that AI systems used throughout recruitment, evaluation, promotion and retention may perpetuate historical patterns of discrimination, including discrimination against women (Regulation (EU) 2024/1689).

The regulatory treatment of employment-related AI is relevant to this study because it shifts attention from whether AI is inherently discriminatory towards the conditions under which consequential systems are governed. For high-risk AI systems, the EU framework includes requirements concerning risk management, data governance, transparency and human oversight. These mechanisms are important because an algorithmic score or recommendation should not necessarily be treated as a complete representation of an individual's suitability for employment or advancement. A numerical assessment may provide

useful information, but the interpretation of that information remains part of the organisational decision-making process.

Human oversight therefore has an important role, although it should not be treated as an automatic solution to algorithmic bias. Human decision-makers can themselves reproduce stereotypes and discriminatory assumptions. The relevant alternative is consequently not a simple choice between biased algorithms and neutral human judgement. Rather, responsible governance requires attention to the relationship between technological assessment and informed human decision-making. Individuals responsible for employment decisions need sufficient understanding of the systems they use, the limitations of their outputs and the contexts from which relevant data are derived. Human oversight is meaningful only when those exercising it are able to question, interpret and, where appropriate, depart from algorithmic recommendations rather than merely confirming them.

Training and AI literacy are therefore important components of organisational governance. This differs from the discussion of workers' access to digital skills in Section 2.5. Here, the relevant issue concerns the capabilities of those who deploy and interpret AI systems in consequential employment settings. Staff using these systems need not necessarily possess advanced technical expertise, but they should understand that algorithmic outputs are based on particular data, assumptions and objectives and that apparently precise scores do not eliminate the need for contextual and professional judgement. Following the 2026 amendment to Article 4 of Regulation (EU) 2024/1689, providers and deployers are required to take measures to support the development of AI literacy among staff and other persons operating or using AI systems on their behalf, taking account of their technical knowledge, experience, education and training, the context of use, and the persons or groups on whom the systems are used. The amended provision also clarifies that this obligation does not require providers or deployers to guarantee a specific level of AI literacy for each individual (Regulation (EU) 2024/1689, Art. 4, as amended by Regulation (EU) 2026/1744).

At the same time, organisational responsibility should extend beyond the judgement of an individual human resources manager. Where patterns of disadvantage repeatedly appear in recruitment, promotion or workplace decisions, organisations should be capable of examining whether these patterns are connected to the design, data or use of an AI system. Transparency, monitoring, documentation and opportunities to review consequential decisions can therefore help identify problems that may not be visible from individual outcomes alone. The purpose of such scrutiny is not to guarantee identical outcomes for women and men, but to assess

whether technological systems are contributing to the reproduction of barriers that prevent individuals from competing under substantively equal conditions.

This distinction is central to the relationship between AI governance and women's economic independence. A woman may possess the digital skills necessary to participate in an AI-transformed labour market and may formally have access to employment opportunities, yet still encounter disadvantage if systems involved in allocating those opportunities reproduce structural inequalities embedded in previous employment patterns. Conversely, AI-assisted decision-making may also provide opportunities to make employment processes more systematic and to identify patterns that human decision-makers might otherwise overlook. The effects are therefore not predetermined by the technology itself.

The evidence on employment decision-making directs attention to three connected issues: the construction of algorithmic outputs, the capacity of human decision-makers to interpret them critically and the possibility of examining their effects after deployment. Human involvement does not resolve bias when decision-makers defer to automated recommendations or lack the information needed to challenge them. This section therefore locates algorithmic decisions within labour markets already shaped by unequal access to education, experience, professional advancement and caring resources, providing the evidentiary basis for the governance analysis developed in Chapter 3.

2.7 Women's Economic Independence and Financial Security

The previous sections have examined how AI may affect access to employment, exposure to occupational change, digital skills and employment-related decision-making. These developments matter for women's economic independence, but employment itself should not be treated as equivalent to economic independence. A woman may be employed and receive an income while remaining financially insecure because her earnings are insufficient or unstable, because she has limited capacity to accumulate assets, or because she has limited control over financial resources. The European Institute for Gender Equality (EIGE, 2024) therefore argues for a multidimensional understanding of financial independence that connects income with wealth and with power and control over economic resources. This broader approach is useful for assessing the economic implications of AI because it shifts attention from whether women participate in the labour market to the quality and durability of the economic position that such participation provides.

Financial security is particularly important within this broader concept. Regular earnings can strengthen an individual's ability to meet everyday needs, plan for the future and reduce

reliance on others, but the existence of earnings alone does not establish that these conditions are secure. EIGE (2024) finds persistent gender inequalities not only in pay and earnings but also in wealth, while noting that inequalities can accumulate across the life course. Consequently, changes in work associated with AI need to be considered not only in relation to immediate employment outcomes but also in relation to their possible effects on the stability of income and the longer-term capacity to build economic resources.

This distinction also changes how the economic benefits of AI should be evaluated. Productivity gains at the level of a task, firm or economy do not necessarily show who ultimately receives those gains. Emerging empirical evidence indicates that productivity improvements associated with generative AI are real in some settings but uneven, and have not yet consistently translated into higher measured earnings or employment for workers (Merola et al., 2026). The relationship between technological productivity and individual financial security is therefore not automatic. An organisation may become more productive without the resulting economic gains being distributed proportionately among workers, just as a worker may remain employed while experiencing changes in hours, responsibilities, bargaining position or prospects for progression.

The distribution of AI-related gains is consequently central to an assessment of economic independence. Fan and Nguyen (2026), using observed AI-usage data across countries, find that the economic value associated with AI use is unevenly distributed across occupations and is particularly concentrated in a relatively narrow group of professional occupations in many developing economies. Their analysis does not provide a gender-specific measure of financial independence, and it should therefore not be interpreted as direct evidence that women receive a smaller share of AI gains. It nevertheless demonstrates an important distributional point: aggregate economic gains from AI can coexist with substantial differences in who is positioned to capture those gains. For a gender analysis, this makes the existing location of women within labour markets relevant to understanding how new economic opportunities may be distributed.

The same reasoning applies to risk. The economic significance of AI cannot be assessed only through the binary outcome of whether a job continues to exist. Changes in the organisation or quality of work may affect financial security even without job displacement. If technological change contributes to less predictable earnings, weaker prospects for progression or other forms of economic insecurity, continued employment may not necessarily preserve the same level of economic independence. Conversely, where AI complements workers, improves productivity, supports progression or expands access to

better-paid work, it may strengthen women's economic position. The direction of the effect is therefore not predetermined by the technology itself.

This perspective is consistent with the theoretical framework developed in Chapter 1. Human Capital Theory draws attention to the skills and experience through which individuals may benefit from new economic opportunities, while Labour Market Segmentation Theory helps explain why those opportunities and rewards may be distributed differently across occupations and sectors. Feminist Political Economy adds a further question: who receives the economic benefits generated by technological change, and who bears its costs and risks? These perspectives together prevent an assessment of AI from stopping at aggregate productivity or employment figures and instead direct attention towards the distribution of economic resources and opportunities.

For women's economic independence, this distributional question is especially significant because financial inequality is cumulative. Differences in earnings can influence the capacity to save, acquire assets and build longer-term financial security. EIGE's (2024) analysis shows why financial independence cannot be reduced to current labour income alone: wealth and control over resources form part of an individual's capacity to maintain economic autonomy over time. Accordingly, an AI-related employment opportunity that produces income may be economically valuable without necessarily providing durable financial independence if the resulting income is insecure or if the individual remains unable to build and control economic resources.

The appropriate question for AI governance is therefore broader than whether technological innovation generates economic growth or increases productivity. It also concerns the conditions under which the benefits of that growth are distributed. Governance choices concerning labour protection, training, social protection, workplace implementation and the management of technological transitions can influence whether productivity gains contribute to broadly shared economic security or remain concentrated among particular groups of workers and owners of capital. This does not imply that equal economic outcomes must be guaranteed. Rather, it requires attention to whether different groups have meaningful opportunities to benefit from technological change and whether the risks of that change are disproportionately transferred to those already in less secure economic positions.

The evidence reviewed across the chapter therefore requires employment outcomes to be connected to the stability, control and long-term security of economic resources. Job creation or productivity growth can improve one dimension while leaving income volatility, asset

accumulation or control over resources unchanged. Economic independence provides the distributional endpoint of the pathway mapped in Sections 2.1–2.6 and links those labour-market patterns to the inventory of governance frameworks examined in the following section.

2.8 AI Governance and Gender Equality Policies

The preceding sections have shown that the relationship between Artificial Intelligence and women's economic independence is shaped by more than the technical characteristics of AI systems. Representation in AI development and governance, decision-making power, employment opportunities, occupational transformation, access to skills, algorithmic employment decisions and financial security all operate within labour markets and societies that were already characterised by gender inequalities before the widespread adoption of AI. The final question for this chapter is therefore whether AI governance frameworks are capable of recognising these conditions and responding to them in ways that support gender equality.

A formally gender-neutral approach to AI governance is not necessarily sufficient for this purpose. Prohibiting discrimination and applying the same rules to women and men are important protections, but identical treatment does not by itself address unequal starting conditions. Gender-responsive governance requires attention to the possibility that apparently neutral technologies may operate differently across groups because they are introduced into unequal social, educational and economic contexts. This does not mean that every unequal outcome should automatically be classified as discrimination. Rather, it means that governance frameworks should be capable of identifying differentiated effects, examining their causes and determining whether technological systems are reproducing or intensifying existing barriers.

The UNESCO Recommendation on the Ethics of Artificial Intelligence provides one of the clearest international examples of this broader approach. Its policy framework treats gender as a distinct area of action while also calling for a gender perspective to be integrated across AI governance. UNESCO recommends that national digital policies include gender action plans and that Member States consider targeted programmes to increase girls' and women's participation in science, technology, engineering and mathematics, including ICT. It also links these measures to employability, equal career development and professional growth, while encouraging women's participation and leadership throughout the AI system life cycle (UNESCO, 2021). The framework therefore goes beyond a narrow prohibition of

discriminatory algorithmic outcomes and connects AI governance with the conditions under which women can participate in and benefit from the AI-driven economy.

This connection is important because some of the inequalities encountered in AI-related labour markets originate long before an individual enters employment. Gender stereotypes in education can shape subject choices, expectations and later career pathways. EIGE identifies education and training as important sites in which gender stereotypes can be reproduced and stresses the need to challenge stereotypes in curricula, teaching practices and institutional approaches (EIGE, n.d.). These inequalities cannot reasonably be corrected only at the point at which an AI system evaluates a job applicant or an employee. By that stage, differences in education, experience, professional networks and occupational pathways may already have accumulated over many years.

This does not imply that AI governance itself should be expected to transform schools, families or cultural norms. Such an interpretation would make the concept of AI governance so broad that it would lose analytical usefulness. A more appropriate conclusion is that gender-responsive AI governance must be coordinated with wider policies concerning education, skills, labour markets, care and gender equality. UNESCO's approach illustrates this relationship by connecting AI policy with targeted educational and economic measures rather than treating technological regulation as an isolated policy field (UNESCO, 2021). The distinction is important: AI governance can respond to inequalities that become relevant in the development and deployment of AI, but it cannot by itself remove all the structural conditions through which those inequalities were produced.

The labour-market evidence examined by the International Labour Organization reinforces the need for this wider policy perspective. Its 2026 research on generative AI, occupational segregation and gender equality emphasises that the consequences of technological change are not predetermined. Policy choices, social dialogue, measures addressing occupational segregation and women's participation in AI-related roles can influence whether AI-supported transformation contributes to decent work and gender equality (ILO, 2026). This shifts the policy question away from a simple choice between accepting or restricting AI and towards the institutional conditions under which it is introduced into workplaces and labour markets.

At the regulatory level, the European Union Artificial Intelligence Act provides significant safeguards relevant to gender equality even though it is not, as a whole, a gender equality policy. As discussed in earlier sections, Regulation (EU) 2024/1689 classifies

specified employment-related AI systems as high-risk and establishes requirements concerning risk management, data governance, transparency and human oversight. Recital 57 specifically recognises the possibility that AI systems used in recruitment, evaluation, promotion and retention may perpetuate historical patterns of discrimination, including against women. These provisions demonstrate that existing regulation can address important mechanisms through which AI may affect gender equality without assuming that AI is itself the original source of the inequality.

At the same time, the scope of legal safeguards should not be overstated. For example, the fundamental rights impact assessment established by Article 27 of Regulation (EU) 2024/1689 does not impose a universal assessment obligation on every organisation using every high-risk employment system. Its application depends on the categories of deployers and systems specified by the Regulation. This illustrates a broader distinction between recognising fundamental-rights risks in an AI regulatory framework and adopting a comprehensive gender-responsive policy capable of addressing structural inequalities across education, employment and economic participation. The two approaches can complement one another, but they should not be treated as equivalent.

Gender-responsive governance also requires implementation capacity. Ethical principles or legal protections have limited practical value if organisations and public authorities lack the expertise, resources or institutional mechanisms needed to apply them. UNESCO's 2026 assessment of the legal dimension of AI governance identifies continuing gaps between formal alignment with ethical principles and implementation and enforceability in national governance systems (UNESCO, 2026). Meaningful governance therefore requires not only rules but also monitoring, institutional capacity, participation, accountability and mechanisms through which affected groups can raise concerns and influence how AI systems are governed.

The role of participation should nevertheless be understood consistently with the distinction developed earlier in this chapter. Increasing women's numerical representation is important, particularly where women remain excluded from AI-related fields and decision-making, but representation alone does not guarantee gender-responsive outcomes. Conversely, a policy cannot be considered fully inclusive merely because it contains protective provisions for women while women remain persistently absent from the institutions in which technological priorities are defined. Gender-responsive governance therefore requires attention both to substantive outcomes and to the conditions under which women can participate meaningfully in shaping AI policy, development and implementation.

The long-term dimension of gender equality also limits what can reasonably be expected from AI policy. Educational choices, occupational segregation, caring arrangements and social expectations are produced through institutions and cultural practices that may change slowly. Policies aimed at widening participation in STEM, challenging stereotypes or improving women's access to professional advancement may therefore require sustained intervention over time, and their effects cannot be guaranteed in advance. This uncertainty is not an argument against such policies. Rather, it suggests that gender-responsive AI governance should combine immediate safeguards against discriminatory or harmful technological practices with longer-term coordination across policy areas that shape women's opportunities before they encounter AI systems in education or employment.

The analysis in this chapter therefore supports a distinction between gender-neutral and gender-responsive AI governance. The former may provide formally equal rules and prohibit discriminatory treatment. The latter asks an additional question: how do AI systems interact with existing inequalities, and what institutional measures are necessary to prevent those inequalities from being reproduced through technological change? Answering this question requires attention to representation, decision-making power, labour-market structure, skills, employment decisions and the distribution of economic benefits, rather than relying on technological neutrality alone.

Chapter 2 has mapped the empirical patterns, institutional conditions and formal governance instruments relevant to women's economic independence; it has not established that existing responses are adequate or that the mechanisms operate uniformly across contexts. Chapter 3 takes up that unresolved task. It synthesises the patterns identified here through the lenses of power and institutional responsibility and uses illustrative regulatory decisions and implementation evidence to examine whether procedural commitments can detect, correct and remedy the inequalities documented in this chapter.

Chapter 3

Gendered Power Relations in the Governance of AI

Chapter 2 mapped the available evidence on women's position across representation, employment opportunity, occupational change, access to skills, algorithmic workplace decisions, financial security and existing policy frameworks. This chapter does not reproduce that evidence map. It brings those patterns together through the lenses of power and institutional responsibility and asks whether governance arrangements can identify and respond to the inequalities documented in Chapter 2. Illustrative regulatory decisions and implementation evidence are used to test broader claims about participation, accountability, correction and remedy rather than to establish a universally applicable governance model.

3.1 Gendered Power Relations in the Governance of AI

Women's representation in AI governance is an important dimension of gender equality because participation in technological development and governance provides access to institutions in which priorities, risks and responses are defined. Persistent underrepresentation therefore matters in its own right: it reflects unequal access to positions of authority and may narrow the range of experiences represented in decisions about technologies with growing economic and social consequences. Feminist approaches to AI governance place participation alongside broader questions concerning the distribution of power, resources and control within the AI ecosystem (Ricaurte, 2024; Attard-Frost, 2025).

Research on women's political representation provides a useful, although not directly transferable, perspective on this relationship. The distinction between descriptive representation—women's presence in institutions—and substantive representation—the advancement of women's interests—shows why numbers can have political significance. Wängnerud's (2009) review finds mixed empirical evidence on the relationship between the two, while also concluding that, across a broad body of research, women politicians contribute to strengthening the position of women's interests. The implication is not that numerical representation is merely symbolic. Greater representation can alter whose experiences enter institutional debate and who participates in defining priorities.

The debate over "critical mass" further demonstrates why the relationship between numbers and influence should not be treated mechanically. A threshold of approximately 30 per cent has often been proposed as the point at which women may begin to exercise greater influence. Dahlerup (1988), however, questioned the assumption that reaching a particular numerical threshold automatically produces institutional change and proposed greater attention to "critical acts": the actions through which actors mobilise resources, build alliances

and generate change. Later reviews similarly describe the critical-mass concept as contested rather than an established numerical rule (Wängnerud, 2009).

This debate is useful for AI governance because it directs attention to the relationship between presence and influence. Women may participate at different points of the AI lifecycle —as developers, managers, policymakers, regulators or members of oversight bodies—but these positions do not necessarily carry equivalent authority. Power also operates through agenda-setting: defining which problems deserve attention, which risks are prioritised, what evidence counts and whose experiences are considered when technological impacts are evaluated. Ricaurte (2024) links feminist AI governance to precisely these structural questions, including the concentration of control over AI systems, infrastructure, data and knowledge. Attard-Frost (2025) similarly identifies power asymmetries and exclusionary norms as central concerns for AI governance.

For this thesis, the relationship between gender and power in AI governance can therefore be examined through three connected questions. Who is represented in the institutions and processes governing AI? Who has the capacity to shape priorities and decisions within those processes? And to what extent are gendered inequalities and differentiated impacts recognised when AI-related risks and opportunities are assessed? These questions correspond to representation, decision-making power and gender responsiveness, but they are used here as analytical questions rather than as a new theoretical framework.

This distinction also prevents gender-responsive governance from being reduced to the identity of individual decision-makers. Women do not constitute a homogeneous category with identical interests, and feminist scholarship on representation has challenged the assumption that female representatives necessarily advance a predetermined set of women's or feminist claims (Celis & Childs, 2012). An intersectional perspective strengthens this point: class, race and ethnicity, migration status, education, geographical location and caring responsibilities shape both women's access to positions of authority and their experiences of technological change. The question is therefore not simply whether women are present, but which women participate, what influence they exercise and which gendered experiences become visible in governance processes.

Seen in this way, representation and power are neither competing explanations nor interchangeable measures. Women's representation is itself an equality issue and can contribute to substantive change; the distribution of decision-making authority determines how far participation can translate into influence; and gender responsiveness concerns the

content and consequences of governance decisions. Examining these dimensions together allows the thesis to move from who participates in AI governance to how participation can shape the distribution of the economic opportunities and risks associated with AI. This provides the direct link to the next section, which examines AI as a potential source of economic opportunity for women.

3.2 AI as a Source of Economic Opportunity for Women

Artificial intelligence can expand the range of tools available for learning, problem-solving, idea development and professional work. These capabilities are not inherently gender-specific: women and men can both use generative AI to acquire knowledge, perform tasks and develop new forms of economic activity. However, access to a useful technology does not by itself constitute economic opportunity. From the perspective of women's economic independence, AI becomes economically significant when its use can be converted into professional advancement, income, greater bargaining power or more secure participation in the labour market. The relevant gender question is therefore not simply whether women can access AI, but whether they can transform its capabilities into meaningful economic gains.

Evidence from the workplace confirms that generative AI can strengthen workers' capabilities in certain contexts. Brynjolfsson, Li and Raymond (2025) studied 5,172 customer-support agents and found that access to an AI assistant increased productivity by 15 per cent on average, with larger gains among less experienced and lower-skilled workers. The study also found evidence of faster learning. Although these findings are not gender-specific, they demonstrate a mechanism through which AI may create economic opportunity: it can help workers perform some tasks more effectively and acquire relevant knowledge more quickly. This evidence establishes the existence of a potential benefit, but it does not show who will ultimately obtain that benefit or whether improved performance will alter workers' economic position.

The distinction between capability and economic outcome is essential. Increased productivity does not automatically produce higher wages, promotion, employment security or economic independence. Reviewing emerging empirical research, Merola et al. (2026) conclude that the productivity effects of generative AI are real but uneven and that reported time savings have not yet consistently translated into higher measured output, earnings or employment. The economic value generated through AI may be retained by employers, absorbed through increased workloads or distributed unequally among workers. Economic opportunity should therefore be assessed by examining not only whether AI improves

performance, but also whether workers receive a meaningful share of the value that the technology helps them create.

Women may encounter inequality before this process of economic conversion even begins. Aldasoro et al. (2024) found that 50 per cent of men in their United States sample had used generative AI during the previous twelve months, compared with 37 per cent of women. Differences in income, education, age and race explained only a small part of the gap, while self-assessed knowledge of generative AI was the most important explanatory factor. Privacy concerns, trust and perceptions of employment-related risks and benefits also contributed. These findings suggest that the formal availability of AI does not ensure equal adoption. If familiarity with AI becomes increasingly relevant to professional learning and career development, unequal adoption can affect who is positioned to benefit from AI-assisted work.

Yet the problem cannot be reduced to women's knowledge, confidence or willingness to adopt a new tool. Women and men encounter AI from different social and occupational positions. Gender stereotypes that present mathematics and technology as masculine fields, or that direct women towards supposedly lighter or more 'appropriate' forms of work, influence educational aspirations and career choices long before an individual begins using AI. OECD research connects gender norms and cultural constructs with differences in confidence, fields of study and later employment opportunities, despite relatively small gender differences in actual performance in mathematics and science (OECD, 2023). Women's underrepresentation in AI-related occupations, also identified by the ILO (2026), must therefore be understood partly as the result of earlier social and institutional processes. A framing that presents AI as an opportunity requiring women simply to acquire more skills risks shifting responsibility onto individual women while leaving these structural conditions unexamined.

This analysis changes the role assigned to policy. Encouraging women to use generative AI may be useful, but adoption alone cannot guarantee economic empowerment. Policy measures must address the conditions that determine whether AI use can produce lasting economic benefits. These include challenging gender stereotypes in education and career guidance, providing accessible AI and digital-skills training, improving women's entry into AI-related and other high-value occupations, and requiring employers to provide equitable access to workplace technologies and training. Concerns regarding privacy and trust also require credible data protection, transparency and channels through which workers can question or contest the use of AI in the workplace. Finally, productivity gains should be connected to fair wages, career progression and employment security if technological

improvement is to strengthen workers' economic position rather than only organisational performance.

AI can therefore be a source of economic opportunity for women, but equal access to the technology is an inadequate measure of that opportunity. What matters is women's capacity to convert AI-enabled capabilities into income, career progression, bargaining power and meaningful economic independence. This capacity is shaped by adoption, education and skills, but also by social expectations, occupational structures, employment practices and policy choices. Gender-responsive AI governance should consequently evaluate not only whether women are exposed to or use AI, but also who controls the technology, who captures the value it generates and whether women obtain a fair share of its economic benefits. Without these conditions, AI may expand the theoretical range of opportunities while reproducing inequality in the ability to realise them.

3.3 AI as a Potential Driver of Labour Market Exclusion

The economic opportunities associated with artificial intelligence do not arise in a neutral or equally accessible labour market. They enter institutions already structured by occupational segregation, unequal care responsibilities, differences in contractual security, and gendered assumptions about suitable work. Labour-market exclusion should therefore be understood more broadly than unemployment: it may involve losing access to an entry route, being filtered out of recruitment, remaining in work under more intensive or insecure conditions, or lacking a realistic route to adapt as tasks change. To connect these outcomes rather than treat them as separate risks, this section follows three stages of a worker's position in the labour market: access to employment, conditions within employment, and capacity to adapt. The argument is cumulative. A disadvantage at one stage can reduce the resources available to overcome the next, so the relevant question is how AI-mediated changes interact across a working life, not whether one technology directly excludes all women in the same way.

Occupational segregation provides the starting condition for the first stage: access to employment. As discussed in Section 2.4, women's concentration in clerical, administrative, and business-support occupations places many female workers in jobs whose tasks are highly susceptible to generative AI. Exposure is not equivalent to job loss. The International Labour Organization emphasises that generative AI is more likely to transform tasks, skills, and working conditions than to eliminate most occupations, while the emerging empirical literature has not established widespread displacement (Bardak et al., 2026; Merola et al., 2026). Nevertheless, stable aggregate employment can conceal a narrowing of routes into

work. Clerical and administrative jobs have historically allowed women and younger workers to acquire experience, organisational knowledge, and credentials. Gmyrek, Viollaz and Winkler (2026) describe a possible ‘white-collar bypass’ in which generative AI is adopted before economies expand these intermediate office-based roles. The resulting risk is not simply that an existing worker is replaced, but that a potential worker never obtains the first position from which a career could develop.

Algorithmic recruitment can reinforce or partly counter this contraction of entry routes. Systems used for advertising, screening, and ranking applicants can widen the pool of candidates, standardise procedures, and reduce some forms of inconsistent human judgement. They can also reproduce disadvantage through historically patterned data, proxy variables, inappropriate prediction targets, or unrepresentative evaluation datasets (Köchling & Wehner, 2020; Fabris et al., 2025). Lambrecht and Tucker’s (2019) field experiment illustrates that unequal access does not require an explicit instruction to discriminate: a gender-neutral advertisement for STEM careers reached fewer women because cost-optimising delivery made women in the relevant age group more expensive to reach. At the same time, the existing literature does not justify the general claim that algorithmic hiring is always more biased than human hiring. Fabris et al. (2025) show that the comparison depends on the system, the baseline, the fairness criterion, and the organisational context. The more precise concern is therefore accountability at the point of entry: applicants may be denied an opportunity without knowing which automated process affected them or possessing the information needed to challenge its validity.

The second stage concerns the quality and distribution of power within employment. Algorithmic management systems allocate tasks, monitor activity, assess performance, schedule labour, and influence rewards or continued employment. Such systems may improve coordination, increase consistency, or make flexible work possible. Their benefits, however, do not resolve the risks identified by the OECD concerning surveillance, work intensity, privacy, reduced autonomy, and workers’ limited understanding of automated decisions (OECD, 2023). These risks acquire a gendered dimension where women are concentrated in closely monitored service and administrative roles, or where apparently uniform performance measures ignore interruptions and time constraints associated with care. A metric may be formally identical for every worker while penalising constraints that are unequally distributed. Continued employment under these conditions does not amount to full economic inclusion if workers lose control over time, professional judgement, or the ability to contest decisions that affect their income.

Platform work is a concentrated example of this wider management problem rather than a separate mechanism. It can offer a genuine advantage to women who would otherwise be unable to enter paid work, particularly by lowering geographical barriers and permitting some choice over working time. That benefit should not be dismissed merely because the work is insecure. Yet the European Institute for Gender Equality's study of almost 5,000 platform workers in the European Union shows that flexibility can coexist with unpredictable income, weak social protection, algorithmic control, and difficulties combining paid work with unpaid care (EIGE, 2022). Workers completing fragmented and tightly specified tasks may also receive few opportunities to develop transferable skills or progress within an organisation. The relevant comparison is therefore not between platform work and an ideal secure job that may be unavailable. It is between the immediate access platform work can provide and the longer-term consequences of placing flexibility, income risk, and adaptation costs primarily on the worker.

The third stage is workers' capacity to adapt, where an apparent contradiction with Section 3.2 must be avoided. The adoption gap discussed there concerns the use of generative AI tools: women in the cited study were less likely than men to report using such tools. The evidence considered here concerns participation in adult education and digital training, which is a different outcome. OECD data show broadly similar overall participation by women and men in adult education, while women among the non-participants are more likely to identify family responsibilities as a barrier (OECD, 2025a). These findings can coexist: comparable participation in formal or non-formal training does not imply equal familiarity with generative AI, equal intensity of use, or equal opportunity to convert a tool into career advancement. Nor does offering training settle the problem. Access depends on job characteristics, prior educational advantage, employer-provided learning, time, and financial constraints; adult training systems frequently favour those who are already better positioned (OECD, 2025b). Reskilling can therefore reduce exclusion only when workers can undertake it through paid time, accessible scheduling, care support, and credible pathways into actual jobs.

Seen across these three stages, AI-related exclusion is best understood as a sequence of compounding filters. Occupational change may narrow an entry route; automated recruitment may make the remaining route harder to see or contest; algorithmic management may reduce autonomy and transfer risk after entry; and inaccessible adaptation opportunities may then limit movement into better positions. No single mechanism proves that women as a group will be excluded, and each can produce benefits in particular settings. The stronger finding is that apparently modest disadvantages at different stages can accumulate for the same workers,

especially where occupational segregation and unpaid care already constrain their options. This diagnosis also produces more specific institutional requirements than a general appeal to ‘better governance’: preserve entry-level and developmental functions when work is redesigned; audit advertising and selection outcomes; disclose and review consequential employment decisions; protect autonomy, privacy, and social protection in digitally managed work; and make reskilling practically accessible. The test is whether women can enter, remain in, and progress through changing labour markets, rather than whether an AI system appears neutral when examined at only one point in that process.

3.4 The Link Between Economic Independence and Gender-Based Vulnerability

This section examines a specific and indirect connection between AI and gender-based vulnerability. The available literature does not provide direct evidence that AI-mediated employment or AI-related income changes intimate partner violence outcomes. Research on AI-facilitated abuse, such as surveillance, impersonation, or image-based violence, addresses a different pathway and falls outside the economic focus of this thesis. The claim developed here is therefore not that AI causes or prevents violence. It is that AI-driven labour-market change may alter one condition that shapes women’s options in abusive situations: access to secure and controllable economic resources. The analysis combines two bodies of evidence - research on AI and work, considered in Sections 3.2 and 3.3, and research on economic resources and intimate partner violence - while keeping the absence of direct causal evidence visible.

The second body of evidence establishes why the economic consequences of AI may matter, but it should be stated briefly. A meta-analysis of 19 randomised controlled trials involving 44,772 participants found that economic empowerment interventions were associated, on average, with lower emotional, physical, and sexual intimate partner violence (Eggers del Campo & Steinert, 2022). Yet income and independence are not equivalent. Economic abuse includes interference with employment, confiscation of earnings, coerced debt, restriction of access to bank accounts, and other conduct that limits a person’s ability to acquire, use, or maintain resources (Johnson et al., 2022). A woman may consequently be employed without controlling her wages, accumulating savings, or possessing the practical means to leave. For the purposes of this section, economic independence therefore means access to resources that are sufficiently stable and under the woman’s control, rather than labour-market participation by itself.

The possibility of backlash prevents this relationship from being treated as a simple protective formula. Stöckl et al. (2021) analysed cross-sectional Demographic and Health Survey data from countries in sub-Saharan Africa; their results are regional and correlational, not evidence of a universal causal pattern. Within that dataset, education and household wealth were associated with lower intimate partner violence, while some configurations of women's employment - particularly where only the woman worked or earned more than her partner - were associated with higher violence. This finding exposes a genuine conflict: greater resources may widen a woman's options while simultaneously challenging an unequal distribution of authority within the household. The protective effect of income cannot therefore be assumed in advance or separated from coercive control, gender norms, accessible services, and social protection (UN Women, 2023). Economic change can alter power, and the response to that alteration is itself part of the outcome that must be examined.

Violence can also damage the economic position on which greater autonomy depends. Studies associate domestic or intimate partner violence with workplace disruption, unemployment, job instability, and reduced economic wellbeing (Showalter, 2016; Lindhorst et al., 2007; Adams et al., 2012). These studies provide evidence mainly for the direction from violence to economic harm. They do not empirically trace a complete feedback loop in which economic loss then produces further violence. Any account of a self-reinforcing cycle must therefore be presented as a theoretical synthesis: violence may weaken employment and income; weaker resources may narrow the practical possibilities for obtaining safety; and that constraint may prolong exposure to an abusive situation. The evidence supports the component relationships more strongly than it supports the full sequence as a single tested mechanism.

Against this background, AI-related labour-market change creates three analytically relevant pathways. First, augmentation or new forms of work may improve earnings and career continuity, potentially expanding the resources available for independent decisions. Second, displacement, the erosion of entry-level work, or exclusion through algorithmic recruitment may reduce access to those resources. Third, algorithmic management and platform work may increase labour-market participation while leaving income unpredictable, social protection weak, and control over working time limited (EIGE, 2022; OECD, 2023). These pathways have different implications for substantive independence. A flexible digital job may provide immediate income but still be an unreliable basis for securing housing or planning an exit. Conversely, AI-supported work that produces stable earnings, recognised skills, and progression may be more consequential than a numerical increase in participation.

None of these propositions demonstrates an effect on violence; they identify the economic channels through which such an effect could plausibly arise and the outcomes that future empirical research would need to measure.

The relevance of gender-based vulnerability to AI governance is therefore narrower than the previous version of this argument suggested. AI systems and policies should not be credited with reducing vulnerability merely because they create jobs for women, nor should employment losses be treated as evidence that violence will necessarily increase. The defensible standard is whether AI-related changes strengthen or weaken women's command over stable resources, access to social protection, and realistic exit options. Evaluations should distinguish employment from economic control and should measure job security, earnings volatility, access to benefits, progression, and the worker's ability to retain and use income. This section thus identifies a research gap as well as a policy concern: the connection between AI-mediated work and gender-based violence remains untested, but conventional employment indicators alone are insufficient for assessing whether AI contributes to the form of economic independence that can reduce vulnerability.

3.5 Can AI Governance Promote Gender Equality?

AI governance can promote gender equality, but its contribution should not be inferred merely from the existence of ethical principles, impact assessments, audits, or participatory procedures. A stronger test is whether governance produces an observable change in the distribution of economic opportunities or provides an effective response when unequal outcomes occur. For the purposes of this thesis, gender-responsive AI governance therefore requires three connected functions: it must detect gendered disparities in access or outcomes; create authority and incentives to correct them; and provide an accessible means of challenge or remedy. This standard makes the claim empirically contestable. A governance regime that produces assessments and transparency reports but cannot demonstrate correction, accountability, or redress should not be treated as having promoted gender equality.

The distinction is especially important in relation to algorithmic job advertising. As discussed in Chapter 2, Lambrecht and Tucker's field experiment showed that an advertisement intended to encourage women to enter STEM careers was delivered disproportionately to men, even though the advertiser had not requested gender-based targeting. This example demonstrates why governance cannot concentrate exclusively on the advertiser's intention, the formal neutrality of an advertisement, or the variables explicitly entered into a platform. It must examine the distributional outcome: which groups actually

received information about the economic opportunity. An appropriate equality audit would therefore compare delivery rates across women and men with relevant characteristics, investigate substantial disparities, and require correction where the platform's optimisation process reproduces occupational stereotypes or unequal advertising costs (Lambrecht & Tucker, 2019).

A subsequent regulatory case illustrates how this outcome-based approach can operate in practice. In Decision No. 2025-182, the French Défenseur des droits examined an experiment in which employment advertisements were configured for broadly neutral distribution among adult users. Nevertheless, an advertisement for an early-childhood position was delivered to women in 94 per cent of cases, while an advertisement for pilots was delivered to men in 85 per cent of cases. The authority concluded that the platform's distribution system constituted indirect discrimination based on sex and recommended measures to guarantee non-discriminatory delivery. Crucially, the decision did not require proof that the advertiser had deliberately excluded women or men; the unequal distribution generated by the platform was itself legally relevant. This directly addresses the mechanism identified by Lambrecht and Tucker and shows that existing equality law can be used to scrutinise the outputs of an algorithmic delivery system (Défenseur des droits, 2025).

Detection, however, is not equivalent to demonstrated correction. The French authority requested that the companies report within three months on the measures taken, but the available decision establishes a finding and recommendation rather than evidence that subsequent delivery outcomes became more equal. This distinction supplies a concrete evaluative standard: the intervention should be assessed by comparing sex-disaggregated delivery patterns before and after corrective measures. If the same occupationally gendered distribution persists, the governance response has identified discrimination but has not yet promoted equality. Participation is relevant within this process, but not as an independent achievement. Women's organisations and equality bodies contribute by identifying harms, supplying evidence, and challenging the platform; their participation becomes substantively meaningful only when it can initiate investigation, influence the corrective measure, or support access to a remedy.

The experience of New York City's Local Law 144 further demonstrates why a legal requirement to audit cannot itself serve as evidence of equality. The law prohibits covered employers and employment agencies from using automated employment decision tools unless the tool has received a recent bias audit, a summary has been made public, and candidates have received the required notice (New York City Department of Consumer and Worker

Protection, 2023). Yet Wright et al.'s study of 391 employers located only 18 published audit reports and 13 transparency notices. Because employers retained substantial discretion to determine whether their systems fell within the law's scope, the researchers could not classify the absence of an audit as proof of non-compliance - a condition they termed 'null compliance.' They consequently could not determine whether the regime was reducing employment discrimination. The significance of this case is not that auditing is necessarily ineffective. Rather, it shows what must be measurable for an audit regime to support a gender-equality claim: which employers and systems are covered, whether sex-disaggregated outcomes are examined, what corrective action follows an adverse result, and whether disparities decline over time (Wright et al., 2024).

This outcome-based standard also clarifies the limits of system-specific governance in addressing the broader labour-market changes examined in Section 3.3. As Section 2.8 established, Article 27 of the EU AI Act does not create a universal fundamental-rights impact-assessment duty for every private employer deploying a high-risk employment system. Its obligation applies to specified categories of deployers and uses (Regulation (EU) 2024/1689). More fundamentally, an assessment focused on the risks created by one system may detect discriminatory recruitment or promotion decisions, but it is less suited to identifying 'white-collar bypass': the reorganisation or disappearance of entry-level tasks through which workers previously acquired experience and progressed professionally. No single rejected applicant or biased model necessarily reveals that structural change. Governance of this risk therefore requires sectoral monitoring of hiring patterns, entry-level vacancies, occupational transitions, and access to reskilling, disaggregated by sex. This does not replace system-level assessment; it addresses a different level of harm.

The answer to the question posed by this section is consequently conditional but not unfalsifiable. AI governance can be said to promote gender equality only where evidence shows that it has changed unequal access, allocation, or employment outcomes, or has enabled an effective remedy when such outcomes occur. The French job-advertising decision demonstrates that algorithmic distribution can be tested against sex-equality standards and formally recognised as discriminatory. It does not yet demonstrate that the underlying disparity was corrected. The early evidence from New York City, meanwhile, shows that an audit mandate may fail even to produce verifiable information about coverage and compliance. At present, therefore, existing governance arrangements demonstrate an emerging capacity to identify certain gendered harms more clearly than a proven capacity to eliminate them. Their contribution should be evaluated through observable changes in

outcomes, not through the number of principles, audits, consultations, or reports they generate.

3.6 Human Rights, Social Justice, and Gender-Responsive AI Governance

Section 3.5 established an outcome-based test for AI governance: assessments, audits, and consultations matter only when they help identify unequal effects, produce correction, or make an effective remedy available. The present section addresses a different question: what conception of equality should guide those interventions? A governance system could successfully detect a disparity and still adopt an inadequate remedy if its objective is limited to formally identical treatment. Human-rights protection becomes gender-responsive when it uses substantive rather than merely formal equality as its benchmark. This requires attention not only to whether women and men are treated differently by an AI system, but also to whether the intervention changes the institutional and economic conditions that produced the disparity.

CEDAW General Recommendation No. 25 supplies the legal basis for this distinction. It requires states to address gender relations, stereotypes, and institutional structures and to create an enabling environment in which women can achieve equality of results. Those results include comparable income, equality in decision-making, and freedom from violence (CEDAW Committee, 2004). In AI governance, formal equality might require the same selection rule, advertisement settings, or appeal process for women and men. Substantive equality asks a further question: whether those formally neutral arrangements overcome or preserve women's existing disadvantages. The difference is significant because occupational segregation, unequal care responsibilities, and exclusion from professional networks can shape the effects of a system even when sex is absent from its explicit inputs. A formally neutral process may therefore comply with a prohibition on direct discrimination while continuing to distribute opportunities along historically gendered lines.

The French job-advertising case examined in Section 3.5 provides a concrete test. The organisations conducting the experiment configured the advertisements for broadly neutral distribution among adult users. Nevertheless, Facebook delivered an early-childhood advertisement to women in 94 per cent of cases and a pilot advertisement to men in 85 per cent. The Défenseur des droits classified this as indirect sex discrimination and recommended measures guaranteeing non-discriminatory distribution (Défenseur des droits, 2025). This finding satisfies an important element of formal equality: the platform cannot defend a gendered outcome merely because the advertiser did not request gender targeting. Substantive

equality, however, sets a more demanding remedial objective. Equalising the delivery of future advertisements would remove the immediate disparity, but it would not necessarily counter the occupational stereotypes and unequal employment pathways reflected in the platform's optimisation process. CEDAW's equality-of-results standard leaves room for corrective measures designed to expand women's actual access to occupations from which they have historically been excluded, rather than requiring every intervention to reproduce a formally symmetrical distribution.

The same case also provides a measurable account of participation. The regulatory process was not initiated through a company-organised consultation. Global Witness conducted the advertising experiment and, together with Fondation des Femmes and Femmes Ingénieures, filed the complaint that led to the French authority's decision (Global Witness, 2025). Their participation affected the governance process in three observable ways: they defined the suspected harm, generated sex-disaggregated evidence, and activated an equality-law procedure. This is materially different from inviting women to comment on a system whose objectives and deployment have already been decided. For gender-responsive governance, participation should therefore be assessed by the authority participants exercise: whether they can obtain relevant information, produce or contest evidence, initiate review, and influence the remedy. In the French case, civil-society participation succeeded in converting an otherwise invisible delivery pattern into a legally recognised claim of indirect discrimination.

The case also reveals the limits of a single-axis gender analysis. Its published findings compare the aggregate shares of women and men receiving each advertisement. They do not show whether particular groups of women - for example, migrant, racialised, older, or disabled women - encountered different delivery patterns. This is not a minor absence. Crenshaw's analysis of employment discrimination demonstrated that frameworks organised around separate categories of race and sex can erase harms experienced specifically at their intersection (Crenshaw, 1989). Applied to algorithmic advertising, an audit could report improved overall gender parity while the most advantaged women receive the additional opportunities and more marginalised women remain excluded. An intersectional assessment should therefore examine disaggregated combinations of relevant characteristics where data collection is lawful and statistically reliable, supplement small-sample quantitative analysis with qualitative evidence, and provide complaint procedures capable of identifying harms that predefined categories fail to capture. The objective is not to add an unlimited list of

demographic variables, but to test whether the selected comparison groups conceal the disadvantage under investigation.

The Council of Europe Framework Convention clarifies what a general human-rights framework contributes to this process and what it does not resolve. It requires equality and non-discrimination, sufficient information to challenge AI-assisted decisions, access to complaints, procedural safeguards, and preventive or mitigating action following risk assessment (Council of Europe, 2024). The French case illustrates the practical value of this legal floor: an algorithmic distribution outcome was documented, challenged before a competent equality body, and assessed under existing non-discrimination law. The Convention's procedural model can support similar challenges by requiring information and access to review. It does not itself determine whether the appropriate remedy is equal delivery, a targeted corrective measure, or a broader intervention against occupational segregation. That distributive choice requires a substantive-equality analysis. The distinction is observable rather than rhetorical: procedural protection can be evaluated by whether an affected group can bring and substantiate a claim, while substantive equality must be evaluated by whether the remedy improves the position of the disadvantaged group.

Gender-responsive AI governance therefore adds a normative benchmark to the empirical test developed in Section 3.5. Section 3.5 asks whether governance detects a disparity, produces correction, and enables remedy; Section 3.6 asks which disparities are made visible, whose evidence can activate correction, and what result the remedy seeks to achieve. The French decision demonstrates progress on recognition and accountability, but its long-term contribution to substantive equality would require evidence that corrective measures expanded women's access to occupational opportunities without leaving intersectionally disadvantaged women invisible. Gender-responsive governance is thus not another collection of principles. It is an approach that defines equality through the actual position of disadvantaged women, treats civil society as a source of evidence and accountability, and evaluates remedies by their capacity to alter unequal structures rather than merely restore formal neutrality.

3.7 Implications for Policymakers, Businesses, and Educational Institutions

The findings of this thesis alter what policymakers, businesses, and educational institutions can reasonably treat as evidence of gender equality in an AI-mediated economy. Access to an AI tool does not establish economic opportunity; participation in employment does not establish economic independence; an audit does not establish correction; and

formally identical treatment does not establish substantive equality. The principal institutional implication is therefore evidential. Each actor must assess the outcome over which it exercises authority rather than using the completion of an activity - providing training, publishing an audit, introducing an appeal procedure, or creating employment - as a proxy for equality. The relevant evidence differs across institutions, but it must show whether women can convert AI-related change into secure entry, progression, income, control over resources, and an effective capacity to challenge harmful decisions.

The opportunity analysis in Section 3.2 produces the first implication. Generative AI may improve performance and accelerate learning, but evidence of higher productivity does not demonstrate that workers receive higher earnings, promotion, or employment security. Aldasoro et al.'s (2024) finding that women in their sample used generative AI less frequently than men identifies an additional barrier at the beginning of this conversion process. It should not, however, turn the number of women using ChatGPT into an educational policy target. The reported adoption gap is diagnostically valuable because it may reveal differences in knowledge, confidence, trust, privacy concerns, or anticipated professional benefit; it does not establish that use of one commercial product is itself economic empowerment. Educational institutions and employers should therefore evaluate a longer sequence: access to training, completion, demonstrated ability to use and critically evaluate AI, application of that competence in work, occupational entry or progression, and changes in earnings or security. UNESCO's product-independent competency framework supports this broader approach by combining practical application with human agency, ethics, critical assessment, and system design (Miao, Shiohira and Lao, 2024).

The risk of white-collar bypass identified in Section 3.3 has a different implication. Aggregate employment stability cannot reveal whether entry routes are narrowing before unemployment or displacement becomes visible. If administrative and junior professional tasks are reorganised before new workers enter them, a conventional comparison of employment rates may register no immediate loss while women and younger workers lose a pathway through which experience and organisational knowledge were previously acquired (Gmyrek, Viollaz and Winkler, 2026). This risk requires sectoral and occupational monitoring by public authorities, educational institutions, and large employers. The appropriate baseline is the pre-adoption pattern of entry-level vacancies, hiring, internal progression, and occupational transition within the affected sector. Subsequent outcomes can then be compared by sex and, where the data permit, by relevant intersecting characteristics. Equality does not require women to constitute 50 per cent of every occupation. It requires institutions to explain

persistent departures from women's representation in the relevant qualified or affected population and to determine whether AI-related restructuring has widened an existing entry or progression gap.

The French job-advertising decision provides a more immediate benchmark for businesses and regulators. Advertisements configured for broadly neutral distribution nevertheless produced strongly gendered delivery outcomes, including the delivery of a pilot advertisement predominantly to men and an early-childhood advertisement predominantly to women. The implication is not simply that platforms should conduct a general bias audit. It is that equality must be tested at each stage through which an employment opportunity is distributed: the composition of the eligible audience, the people to whom the advertisement is delivered, those who apply, and those who are selected. A delivery share should therefore be assessed against the relevant eligible or qualified population rather than against an automatic 50-50 target. A substantial or persistent divergence requires investigation of optimisation criteria, pricing effects, proxy variables, and the occupational assumptions embedded in delivery. The French case also establishes an institutional division of responsibility: platforms must retain and analyse distribution data, advertisers must not treat formally neutral settings as proof of equal access, and equality bodies need authority to obtain evidence and require corrective action (Défenseur des droits, 2025).

Wright et al.'s (2024) study of New York City's Local Law 144 demonstrates why the existence of an audit requirement supplies an inadequate governance indicator. The researchers identified only a small number of publicly available audit reports and transparency notices among the employers examined, while uncertainty about which systems fell within the law made the absence of an audit difficult to classify. The policy implication is that an audit regime must have an observable denominator. Regulators need to know which employers use covered systems, which systems have been assessed, whether sex-disaggregated outcomes were examined, and what happened after an adverse result. Its performance can then be measured through coverage rates, publication rates, the proportion of assessments containing relevant gender data, the frequency and type of corrective action, and before-and-after changes in the identified disparity. This is more demanding than counting completed audits, but it makes failure identifiable: a regime cannot claim success when neither compliance nor correction can be verified.

The analysis of algorithmic management and workplace adaptation generates a related implication for businesses. Section 3.3 showed that employment may continue while autonomy, privacy, predictable income, or control over working time deteriorates. It also

showed that apparently comparable participation in adult training does not establish equal capacity to adapt, particularly where care responsibilities, scheduling, and access to employer-supported learning differ. Worker consultation and AI training are associated with better reported workplace outcomes, but consultation is not substantively meaningful when workers cannot influence deployment or contest consequential outputs (Lane, Williams and Broecke, 2023). Businesses must therefore evaluate consultation through its consequences: whether concerns led to changes in system design or implementation, whether challenges to automated decisions were reviewed and corrected, and whether training occurred through paid and practically accessible time. For women in insecure or closely monitored work, the relevant employment indicators also include earnings volatility, scheduling predictability, access to social protection, and progression - not continued labour-force participation alone.

These findings also define the limits of each institution's contribution. Education cannot compensate for the disappearance of entry-level employment, and increasing women's AI competence cannot correct an advertising system that does not deliver opportunities to them. A company audit may identify unequal outcomes within one recruitment system but cannot by itself reveal the sector-wide contraction described as white-collar bypass. Public monitoring can identify an occupational disparity but cannot replace the information and complaint mechanisms needed by an individual affected by an automated decision. Responsibility must therefore follow institutional control: educational institutions are accountable for whether learning produces transferable competence and credible occupational pathways; businesses for the distributional consequences of systems they deploy and the working conditions they reorganise; and public authorities for defining coverage, establishing baselines, compelling disclosure, and ensuring correction and remedy.

The practical implication of the chapter is consequently a set of outcome-specific benchmarks rather than a general demand for responsible AI. Opportunity should be evaluated through conversion into earnings, progression, security, and control over resources. Labour-market inclusion should be assessed across entry, conditions within employment, and capacity to adapt. Algorithmic equality requires comparison between the relevant population and the people who receive, obtain, or retain an opportunity. Governance performance requires identifiable coverage, evidence of correction, and accessible remedy. These benchmarks do not predetermine a universal numerical threshold, because the appropriate comparator differs between advertising, recruitment, training, promotion, and occupational restructuring. They do, however, require the comparator, baseline, and trigger for investigation to be specified in

advance. This makes it possible to determine whether an institution has reduced a gendered disadvantage rather than merely completed a procedure associated with equality.

Chapter 4

Conclusion

4.1 Summary of the Study

This study examined how the governance of artificial intelligence influences women's economic independence and gender equality in the changing world of work. It approached AI not as an autonomous force with predetermined social effects, but as a set of technologies embedded in existing institutions, labour markets and distributions of power. The central concern was therefore not simply whether AI creates opportunities or risks for women. It was to identify the conditions that shape who develops and governs AI systems, who can benefit from their use, who bears their economic costs and who has the power to challenge their outcomes.

Economic independence was defined more broadly than access to employment or income. It also included control over economic resources, continuity and security of work, opportunities for professional advancement, bargaining power and the practical capacity to make life choices without economic dependence. This definition allowed the study to examine tensions that employment figures alone may conceal. Access to AI-mediated work may increase earnings or labour-market participation while also introducing insecurity, surveillance or dependence. Conversely, improved economic resources may strengthen women's autonomy without automatically removing the structural and interpersonal constraints affecting their choices.

The theoretical approaches used in the thesis performed distinct analytical functions. Feminist political economy situated AI within gendered divisions of paid work, unpaid care and economic power. Substantive equality shifted the assessment from formally identical treatment towards the actual distribution of benefits, burdens and remedies. Intersectionality challenged the treatment of women as a uniform category by examining how gender interacts with race, class, migration status, disability, age, care responsibilities and contractual position. Feminist approaches to technology and governance connected these inequalities to decisions about system design, optimisation, deployment and institutional control. Together, these approaches provided complementary rather than interchangeable perspectives on the relationship between AI and women's economic independence.

Chapter 1 established the conceptual and structural foundations of the research. It examined economic independence in relation to labour-market segregation, unequal care responsibilities, representation in technological decision-making and wider gendered distributions of power. It showed why formal technological neutrality is an inadequate basis for evaluating AI. When apparently neutral systems operate within labour markets already

marked by unequal employment patterns and social expectations, they may preserve or intensify those inequalities without explicitly using gender as a decision-making variable.

Chapter 2 analysed the mechanisms through which AI may affect women's position in the labour market. These included occupational exposure to automation and generative AI, unequal access to emerging opportunities, algorithmic recruitment and advertising, workplace surveillance and management, and the reproduction of historical inequality through data-driven decisions. The analysis demonstrated that gendered outcomes do not necessarily require discriminatory intention or the direct use of gender data. They may also result from proxy variables, historical datasets, optimisation objectives and institutional practices that appear neutral when considered separately.

Chapter 3 examined these mechanisms through the broader question of gendered power in AI governance. It found credible evidence that AI can improve productivity, support learning and idea generation and create new forms of economic participation. However, evidence of technological capability did not establish that women would obtain an equal share of those benefits. The thesis distinguished, in particular, between lower adoption of specific generative-AI tools and participation in adult education or digital training, where the evidence does not demonstrate a uniform female disadvantage. This distinction showed that unequal familiarity with a particular tool should not be treated as proof of a general lack of skills among women.

The governance analysis used the French decision concerning the gendered delivery of online job advertisements and empirical evidence on New York City's automated-employment audit regime as illustrative tests of broader governance claims. The French case demonstrated how unequal distribution may arise through cost optimisation even when an advertiser does not directly select candidates by gender. The New York evidence showed that an audit requirement may generate limited compliance and transparency when reporting and enforcement remain weak. These examples do not establish a universally applicable governance standard. They instead illustrate why assessments of AI governance should examine observable outcomes, relevant comparison groups, opportunities for correction and the accessibility of remedies, rather than relying solely on the formal existence of rules or procedures.

The study also identified limits that the available evidence could not resolve. Most importantly, no direct evidence established whether income or employment obtained through AI-mediated work affects women's exposure to intimate-partner or gender-based violence

differently from other forms of economic participation. The connection developed in Section 3.4 therefore remained an evidence-informed hypothesis rather than a demonstrated causal relationship. The analysis was also limited by its reliance on selected cases from particular jurisdictions and by the uneven availability of gender-disaggregated evidence on AI deployment. Its conclusions should consequently be understood as identifying mechanisms and questions for institutional evaluation, not as demonstrating uniform effects across technologies, sectors or groups of women.

The overall finding is therefore narrower and more testable than the claim that AI is inherently beneficial or harmful to women. Women's economic outcomes are shaped by identifiable decisions concerning system objectives, datasets, comparison groups, workplace participation, transparency, enforcement and remedy. The evidence in this thesis shows how these decisions can distribute opportunities and risks unequally, while also marking areas in which the relationship remains empirically uncertain. Section 4.2 applies this qualified conclusion directly to the main research question and the five sub-questions guiding the study.

4.2 Answers to the Research Questions

This section answers each research question through a distinct finding. The answers are connected but not interchangeable: representation concerns whose knowledge enters technological decision-making; labour-market transformation concerns the distribution of gains and transition costs; algorithmic decision-making concerns the conversion of social inequality into technical classifications; and governance frameworks concern the institutional capacity to identify and correct those effects.

Main Research Question

How does the governance of Artificial Intelligence influence women's economic independence and gender equality in the changing world of work?

The principal finding of this thesis is that AI governance influences women's economic independence by determining whether existing gender inequalities are converted into technical criteria and economic outcomes, or identified and corrected before they become institutionalised. Occupational segregation, unequal care responsibilities and differences in employment security exist before an AI system is deployed. They enter technological systems when past employment patterns become training data, continuous availability becomes a performance indicator, lower delivery costs determine who sees a job advertisement or existing applicant pools become the benchmark for equality. Governance affects the result by

deciding which of these inputs and objectives are acceptable, which population should be used for comparison, what level of disparity requires intervention and whether affected workers can obtain correction or remedy.

The influence of governance is therefore visible at three points in the employment process. It shapes access by affecting who sees and can pursue economic opportunities; it shapes evaluation and control through recruitment, performance management and workplace surveillance; and it shapes the distribution of gains and transition costs when AI increases productivity or reorganises jobs. The central issue is not simply whether governance encourages or restricts AI. It is whether institutions require those deploying AI to account for gendered outcomes rather than leaving individual women to overcome them through greater adaptation, training or technological familiarity.

Sub-question 1

How are women represented in the development, governance, and regulation of Artificial Intelligence, and how does this representation influence AI policies and technological outcomes?

The relevant representational problem is a mismatch between exposure and authority. Women are underrepresented in AI-related occupations and important areas of technological decision-making, while many women work in occupations whose tasks are substantially affected by AI-driven restructuring. Those who are exposed to technological decisions are therefore not necessarily those with comparable authority over their design, deployment or regulation. The consequence is not that male developers inevitably produce discriminatory systems. It is that experiences such as unpaid care, interrupted employment histories, occupational segregation and workplace insecurity may enter governance only after they have produced measurable harm rather than being treated as design and deployment concerns from the outset.

The thesis consequently distinguishes descriptive representation from substantive influence. Increasing women's numerical presence may broaden institutional knowledge, but it does not by itself change optimisation goals, budgetary priorities or enforcement practices. Representation affects technological outcomes when women and affected workers can influence what counts as a relevant risk, which outcomes are measured and what corrective action follows. This finding also limits the recommendation developed under Sub-question 5: participation with decision-making authority is necessary for gender-responsive governance, but it cannot substitute for outcome measurement, enforceable duties or access to remedy.

Sub-question 2

How do AI-driven transformations of labour markets affect women's employment opportunities, economic independence, and long-term economic security?

The labour-market evidence identifies an asymmetry between the creation of technological capability and the distribution of economic benefit. Generative AI can increase productivity, with particularly large gains reported for less-experienced workers. This supports a credible opportunity mechanism: AI may help workers perform unfamiliar tasks, generate ideas and acquire capabilities more quickly. However, these studies do not show that productivity gains are converted into higher wages, secure employment or equal career advancement for women. The adoption gap identified by Aldasoro and colleagues further indicates that even widely available tools may not be used equally, although this gap should not be interpreted as evidence of a general female deficit in digital training or ability.

The principal risk identified by the thesis is not limited to the direct elimination of jobs. AI may also weaken routes into more secure employment through white-collar bypass: entry-level tasks that previously allowed workers to acquire experience and progress may be automated before entire occupations disappear. This is particularly relevant where women are concentrated in administrative, clerical and support roles or have fewer resources to absorb a period of retraining and occupational transition. AI can therefore expand what individual workers are capable of doing while simultaneously narrowing the institutional pathways through which that capability becomes stable employment. Its effect on economic independence depends on who captures productivity gains and who bears the costs of occupational transition.

Sub-question 3

In what ways do algorithmic decision-making systems affect existing gender inequalities in employment and access to economic opportunities?

The distinctive effect of algorithmic decision-making is that it can relocate gender inequality from explicit classification to apparently neutral processes of prediction and optimisation. A system does not need to use gender directly to produce gendered results. Historical employment patterns may be translated into assessments of future suitability; interrupted employment histories may function as proxies for care responsibilities; and optimisation for cost or predicted engagement may determine which groups receive information about employment opportunities.

The French decision on online job advertising and the Lambrecht and Tucker field experiment demonstrate the importance of distribution before formal selection. An employer may define a nominally neutral audience while an advertising platform distributes the opportunity unequally because reaching one gender is calculated to be less expensive. During employment, automated scheduling and performance management can produce a related effect by translating continuous availability into an apparently objective indicator of reliability or productivity. The core finding is therefore that algorithmic discrimination may occur through the allocation of visibility, attention and opportunity, not only through the final acceptance or rejection of an applicant. Evaluating only the formal decision point will consequently miss part of the process through which economic inequality is produced.

Sub-question 4

To what extent do current AI governance frameworks recognise and address the gender-specific challenges arising from AI-driven transformations?

Existing frameworks are strongest in recognising individual rights and procedural risks associated with identifiable systems, but weaker in addressing cumulative and distributive inequalities across labour markets. Human-rights and equality instruments provide broad standards of non-discrimination, substantive equality, participation and remedy. AI-specific regulation adds duties relating to risk management, documentation, transparency, oversight and, for certain actors and systems, impact assessment. These instruments can address discriminatory recruitment or other defined high-risk applications.

Their coverage is less certain where inequality arises before an individual applies for a job, across several interconnected systems or through the gradual reorganisation of occupational pathways. Unequal delivery of job advertisements, the disappearance of entry-level tasks and the cumulative effects of automated management do not always fit easily within a model focused on a single decision, deployer or affected individual. The New York City audit regime further shows that creating a procedural obligation is not equivalent to producing usable information or correction. The principal governance gap is therefore not the complete absence of equality principles. It is the limited capacity to connect those principles to distributive outcomes, appropriate comparison populations and mandatory corrective action.

Sub-question 5

How can more gender-responsive approaches to AI governance contribute to strengthening women's economic independence and promoting gender equality?

The most important contribution of gender-responsive governance would be to transfer responsibility for identifying and addressing unequal effects from individual women to the institutions that design, procure and deploy AI systems. Women should not be expected to compensate for structural inequality merely by becoming more familiar with commercial AI tools or continuously adapting to labour-market disruption. Institutions should instead be required to identify the affected population, examine how opportunities and burdens are distributed and explain disparities against an appropriate comparator. Where outcomes cannot be justified, they should have duties and sufficient authority to alter, suspend or withdraw the system and provide effective remedies.

Three elements are therefore more fundamental than a long list of isolated policy measures. First, outcome measurement must extend beyond formal neutrality and final selection rates to include visibility of opportunities, access to training and promotion, job quality, wages and employment continuity. Second, assessment must lead to corrective power and enforceable consequences; an audit without correction or remedy provides limited protection. Third, participation must involve authority rather than consultation alone. Women and affected workers should be able to influence system objectives, deployment conditions and responses to identified harm.

These priorities expose a genuine tension between participation and accountability. Broader representation may improve the knowledge available to institutions, but it cannot guarantee equality and should not be used to legitimise outcomes that remain unequal. Conversely, technical auditing may identify disparities but overlook harms that institutions have not chosen to measure. Gender-responsive governance therefore requires both situated participation and externally enforceable outcome assessment. Its contribution lies not in guaranteeing that every AI system benefits women, but in making the distribution of economic opportunity and insecurity visible, contestable and subject to correction.

4.3 Main Conclusions

Taken together, the findings lead to a conclusion that is not visible from any single mechanism examined in the thesis: a central function of AI governance is to allocate responsibility for inequality. When an AI system affects access to work, performance evaluation or occupational transition, someone must identify the relevant population, recognise a disparity, explain its causes and decide whether correction is required. Governance can assign these burdens primarily to individual women, who must acquire new skills, discover that they have been disadvantaged, challenge an opaque decision and prove

harm. Alternatively, it can place anticipatory and corrective duties on the institutions that design, procure and deploy the system. This allocation of responsibility is consequential because formal access to technology has limited value when the costs of adaptation and contestation remain individualised.

This conclusion connects the findings on opportunity, algorithmic decision-making, representation and enforcement without collapsing them into a repeated list. An opportunity-centred account can present unequal uptake as a problem of women's confidence or familiarity; an algorithmic account can require an individual applicant to contest a decision she may never see; a representational response can invite women to participate without transferring decision-making power; and an audit regime can document a disparity without obliging anyone to correct it. In each instance, an institutional problem can be reframed as an individual deficit or procedural task. The common risk is therefore not only unequal treatment by a system. It is the privatisation of responsibility for responding to technological change.

A second implication follows from this responsibility problem: the appropriate unit of governance is often the economic pathway rather than an isolated algorithmic decision. Women may be excluded when an opportunity is distributed, when candidates are ranked, when work is scheduled, when performance is evaluated or when entry-level tasks are removed from an occupational route. A system can satisfy a narrow test at one stage while inequality is produced at another. For example, parity among applicants says little about people who never received an advertisement, and a formally equal promotion rule says little about workers whose automated schedules prevented them from accumulating the required experience. Analysis should therefore follow access, selection, working conditions, advancement and transition as connected stages. This does not mean that one institution controls the entire pathway; it means that governance gaps become visible only when responsibility across those stages is mapped rather than assumed.

The tension between participation and accountability cannot be resolved simply by recommending more of both. Participation is necessary because affected workers can identify harms, priorities and forms of dependence that predetermined audit categories may omit. Yet participation can become symbolic when institutions retain control over objectives, metrics and corrective action. Independent assessment creates a different risk: it may produce comparable measurements while excluding experiences that were never translated into measurable variables. The institutional implication is not an uncomplicated merger of the two approaches, but a division of functions that preserves their different strengths. Affected workers and their representatives should have authority to shape the questions and outcomes

examined; independent bodies should verify evidence and compliance; and regulators, employers or deployers should remain responsible for correction and remedy. Whether this arrangement works better than consultation or auditing alone is an empirical question, not a conclusion established by the cases reviewed here.

This synthesis does not create a single new metric called ‘economic independence’. Instead, women’s economic independence operates as a lens that changes what governance must ask. Two questions follow from the analysis. First, who carries the burden of detecting, explaining and correcting an unequal outcome? Second, does the assessment examine the stage of the economic pathway at which opportunity, security or bargaining power may be lost? These questions connect the more specific benchmarks developed earlier in the thesis—including comparator choice, outcome coverage, disclosure and corrective action—without presenting them as a universally validated standard. Their value lies in revealing when procedural compliance leaves the underlying distribution of economic power unchanged.

The remaining research agenda is correspondingly specific. Existing productivity studies identify capability gains, but longitudinal worker-level evidence is needed to determine how those gains affect wages, promotion, job retention and task reallocation by gender. The white-collar bypass hypothesis requires cohort or occupational-panel research tracing whether the removal of entry-level tasks actually reduces progression into secure roles. Audit research should compare results produced by applicant-pool and eligible-population comparators and examine whether disclosure triggers correction. Studies of participation should distinguish consultation from decision-making authority and test whether either changes deployment choices or outcomes. Finally, direct research is required before any claim can be made about whether AI-mediated income or employment changes women’s exposure to intimate-partner or gender-based violence. These are not areas in which the thesis found no evidence at all; they are points at which existing evidence does not establish the longer-term, causal or comparative relationship required.

The final conclusion is therefore institutional rather than technological. AI governance contributes to gender equality when it prevents the risks and adjustment costs of technological change from being treated as problems that individual women must solve alone. This requires attention across the full pathway through which economic opportunities become—or fail to become—secure work, income, advancement and bargaining power. It also requires a visible assignment of responsibility: participation must influence what is examined, independent scrutiny must test institutional claims and identified disparities must reach an actor with the duty and power to correct them. The thesis does not demonstrate that this arrangement has

already been achieved. It shows why the distribution of responsibility is central to judging whether AI-driven change strengthens women’s economic independence or reproduces existing dependence in a new technical form.

References

Adams, A. E., Tolman, R. M., Bybee, D., Sullivan, C. M., & Kennedy, A. C. (2012). The impact of intimate partner violence on low-income women's economic well-being: The mediating role of job stability. Violence Against Women, 18(12), 1345–1367. https://doi.org/10.1177/1077801212474294

Aldasoro, I., Armantier, O., Doerr, S., Gambacorta, L., & Oliviero, T. (2024). The gen AI gender gap. Economics Letters, 241, 111814. https://doi.org/10.1016/j.econlet.2024.111814

Attard-Frost, B. (2025). Transfeminist AI governance. First Monday, 30(4). https://doi.org/10.5210/fm.v30i4.14121

Bardak, U., Pouliakas, K., Hippe, R., Sostero, M., Tasiovasilis, M., Kizu, T., Tumurchudur-Klok, B., Strietska-Ilina, O., Martin Lataix, J. I., Iriarte, R., & Zhang, W. (2026). Changing landscape of skills in the age of AI. European Training Foundation, Cedefop, Eurofound, European Commission, International Labour Organization, & UNESCO. https://doi.org/10.2816/7083675

Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: A systematic literature review. AI and Ethics, 5, 3265–3279. https://doi.org/10.1007/s43681-024-00653-w

Becker, G. S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education. National Bureau of Economic Research.

Berg, J., & Johnston, H. (2025). AI in human resource management: The limits of empiricism (ILO Working Paper No. 154). International Labour Organization. https://doi.org/10.54394/NMSH7611

Breitkreuz, R., Baird, M., Hughes, K. D., & Konnikov, A. (2026). Setting the stage: Women's economic empowerment from a global perspective. In R. Breitkreuz & M. Baird (Eds.), Women's economic empowerment and the state: A critical human ecological approach (pp. 1–29). Edward Elgar Publishing. https://doi.org/10.4337/9781803921174.00009

Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at work. The Quarterly Journal of Economics, 140(2), 889–942. https://doi.org/10.1093/qje/qjae044

Cantillon, S., Mackett, O., & Stevano, S. (2023). Feminist political economy: A global perspective. Agenda Publishing.

Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E. J., & Tavares, M. M. (2024). Gen-AI: Artificial intelligence and the future of work (Staff Discussion Note 2024/001). International Monetary Fund. https://doi.org/10.5089/9798400262548.006

Celis, K., & Childs, S. (2012). The substantive representation of women: What to do with conservative claims? Political Studies, 60(1), 213–225. https://doi.org/10.1111/j.1467-9248.2011.00904.x

Chugunova, M., Harhoff, D., Hölzle, K., Kaschub, V., Malagimani, S., Morgalla, U., & Rose, R. (2026). Who uses AI in research, and for what? Large-scale survey evidence from Germany. Research Policy, 55(2), 105381. https://doi.org/10.1016/j.respol.2025.105381

Collett, C., Neff, G., & Gomes, L. G. (2022). The effects of AI on the working lives of women. UNESCO, Inter-American Development Bank, & Organisation for Economic Co-operation and Development.

Committee on the Elimination of Discrimination against Women. (2004). General Recommendation No. 25 on Article 4, Paragraph 1, of the Convention on the Elimination of All Forms of Discrimination against Women, on temporary special measures. United Nations. https://www.un.org/womenwatch/daw/cedaw/recommendations/General%20recommendation%2025%20(English).pdf

Council of Europe. (2024). Council of Europe Framework Convention on Artificial Intelligence and Human Rights, Democracy and the Rule of Law (CETS No. 225). https://rm.coe.int/1680afae3c

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex: A Black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics. University of Chicago Legal Forum, 1989(1), 139-167. https://chicagounbound.uchicago.edu/uclf/vol1989/iss1/8/

Dahlerup, D. (1988). From a small to a large minority: Women in Scandinavian politics. Scandinavian Political Studies, 11(4), 275–298. https://doi.org/10.1111/j.1467-9477.1988.tb00372.x

De Carvalho, L. L., Buchbinder, F., Da Hora, D. A. B., et al. (2026). Social participation as an ethical criterion for AI governance in public administration. AI and Ethics, 6, Article 177. https://doi.org/10.1007/s43681-026-01010-9

Doellgast, V., Appalla, S., Ginzburg, D., Kim, J., & Thian, W. L. (2025). Global case studies of social dialogue on AI and algorithmic management (ILO Working Paper No. 144). International Labour Organization. https://doi.org/10.54394/VOQE4924

Drage, E., & Mackereth, K. (2022). Does AI debias recruitment? Race, gender, and AI's "eradication of difference". Philosophy & Technology, 35, Article 89. https://doi.org/10.1007/s13347-022-00543-1

Défenseur des droits. (2025). Décision n° 2025-182 du 10 octobre 2025: Diffusion algorithmique d'offres d'emploi par une plateforme en ligne constitutive d'une discrimination indirecte en lien avec le sexe des utilisateurs. https://juridique.defenseurdesdroits.fr/doc_num.php?explnum_id=22988

Eggers del Campo, I., & Steinert, J. I. (2022). The effect of female economic empowerment interventions on the risk of intimate partner violence: A systematic review and meta-analysis. Trauma, Violence, & Abuse, 23(3), 810–826. https://doi.org/10.1177/1524838020976088

European Commission. (n.d.). Navigating the AI Act. Shaping Europe’s Digital Future. Retrieved September 13, 2026, from https://digital-strategy.ec.europa.eu/en/faqs/navigating-ai-act

European Institute for Gender Equality (EIGE). (2022). Artificial intelligence, platform work and gender equality. Publications Office of the European Union. https://doi.org/10.2839/372863

European Institute for Gender Equality (EIGE). (2024). Financial independence and gender equality: Joining the dots between income, wealth, and power. Publications Office of the European Union. https://doi.org/10.2839/055249

European Institute for Gender Equality (EIGE). (n.d.). Education. Gender mainstreaming: Policy areas. European Institute for Gender Equality. https://eige.europa.eu/gender-mainstreaming/policy-areas/education

European Institute for Gender Equality. (2026, June 2). Bringing economic violence into view: Better data for better action in the EU. https://eige.europa.eu/gender-statistics/dgs/data-talks/bringing-economic-violence-view-better-data-better-action-eu

Fabris, A., Baranowska, N., Dennis, M. J., Graus, D., Hacker, P., Saldivar, J., Zuiderveen Borgesius, F., & Biega, A. J. (2025). Fairness and bias in algorithmic hiring: A multidisciplinary survey. ACM Transactions on Intelligent Systems and Technology, 16(1), Article 16. https://doi.org/10.1145/3696457

Fan, R. Y., & Nguyen, H. M. (2026). Aggregate gains from AI and their distribution: Global evidence from usage data (IMF Working Paper No. 2026/147). International Monetary Fund. https://doi.org/10.5089/9798229051279.001

Faulkner, W. (2001). The technology question in feminism: A view from feminist technology studies. Women’s Studies International Forum, 24(1), 79–95. https://doi.org/10.1016/S0277-5395(00)00166-7

Global Witness. (2025). Facebook algorithm breaking the law, French equalities regulator decides. https://globalwitness.org/en/press-releases/facebook-algorithm-breaking-the-law-french-equalities-regulator-decides/

Gmyrek, P., Berg, J., & Bescond, D. (2023). Generative AI and jobs: A global analysis of potential effects on job quantity and quality (ILO Working Paper No. 96). International Labour Organization. https://doi.org/10.54394/FHEM8239

Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M. (2025). Generative AI and jobs: A refined global index of occupational exposure (ILO Working Paper No. 140). International Labour Organization. https://doi.org/10.54394/HETP0387

Gmyrek, P., Viollaz, M., & Winkler, H. (2026). Disruption without dividend? How the digital divide and task differences split GenAI's global impact (ILO Working Paper No. 166). International Labour Organization. https://doi.org/10.54394/00033147

International Labour Organization. (2017). Macroeconomic policy and women's economic empowerment.

International Labour Organization. (2024, October 29). Unpaid care work prevents 708 million women from participating in the labour market.

International Labour Organization. (2025). Artificial intelligence adoption and its impact on jobs: Paper prepared under South Africa's G20 Presidency. ILO.

International Labour Organization. (2026). Gen AI, occupational segregation and gender equality in the world of work (Research brief). International Labour Organization. https://doi.org/10.54394/00033798

International Labour Organization. (n.d.). Algorithmic management in the workplace.

International Labour Organization. (n.d.). Labour market segmentation. Retrieved September 15, 2026, from https://www.ilo.org/topics/employment-security/labour-market-segmentation

International Telecommunication Union. (2025). Facts and Figures 2025: The gender digital divide.

Johnson, L., Chen, Y., Stylianou, A., & Arnold, A. (2022). Examining the impact of economic abuse on survivors of intimate partner violence: A scoping review. BMC Public Health, 22, Article 1014. https://doi.org/10.1186/s12889-022-13297-4

Karagianni, A. (2025). Gender in a stereo-(gender)typical EU AI law: A feminist reading of the AI Act. Cambridge Forum on AI: Law and Governance, 1, e25. https://doi.org/10.1017/cfl.2025.12

Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. Business Research, 13(3), 795–848. https://doi.org/10.1007/s40685-020-00134-w

Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. Management Science, 65(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093

Lane, M. (2024). Who will be the workers most affected by AI? A closer look at the impact of AI on women, low-skilled workers and other groups. OECD Artificial Intelligence Papers, No. 26. OECD Publishing. https://doi.org/10.1787/14dc6f89-en

Lane, M., Williams, M. and Broecke, S. (2023). The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers. OECD Social, Employment and Migration Working Papers, No. 288. OECD Publishing. https://doi.org/10.1787/ea0a0fe1-en

Lindhorst, T., Oxford, M., & Gillmore, M. R. (2007). Longitudinal effects of domestic violence on employment and welfare outcomes. Journal of Interpersonal Violence, 22(7), 812–828. https://doi.org/10.1177/0886260507301477

Merola, R., Ernst, E., Samaan, D., del Rio-Chanona, M., & Teutloff, O. (2026). The impact of GenAI on jobs, productivity and work organization: A review of the empirical evidence. International Labour Organization. https://doi.org/10.54394/00034628

Miao, F., Shiohira, K. and Lao, N. (2024). AI competency framework for students. UNESCO. https://doi.org/10.54675/JKJB9835

National Institute of Standards and Technology. (2023). Artificial intelligence risk management framework (AI RMF 1.0). U.S. Department of Commerce. https://doi.org/10.6028/NIST.AI.100-1

New York City Department of Consumer and Worker Protection. (2023). Automated employment decision tools: Local Law 144 of 2021. https://www.nyc.gov/site/dca/about/automated-employment-decision-tools.page

Organisation for Economic Co-operation and Development (OECD). (2023). Gender, education and skills: The persistence of gender gaps in education and skills. OECD Publishing. https://doi.org/10.1787/34680dd5-en

Organisation for Economic Co-operation and Development (OECD). (2023). OECD Employment Outlook 2023: Artificial intelligence and the labour market. OECD Publishing. https://doi.org/10.1787/08785bba-en

Organisation for Economic Co-operation and Development (OECD). (2024a). Algorithm and Eve: How AI will impact women at work. OECD Publishing. https://doi.org/10.1787/a1603510-en

Organisation for Economic Co-operation and Development (OECD). (2024b). OECD Digital Economy Outlook 2024 (Volume 2): Strengthening connectivity, innovation and trust. OECD Publishing. https://doi.org/10.1787/3adf705b-en

Organisation for Economic Co-operation and Development (OECD). (2024c). To what extent do adults participate in education and training? In Education at a Glance 2024: OECD Indicators. OECD Publishing. https://doi.org/10.1787/c00cad36-en

Organisation for Economic Co-operation and Development (OECD). (2024d). Recommendation of the Council on Artificial Intelligence. OECD Legal Instruments. https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449

Organisation for Economic Co-operation and Development (OECD). (2025a). Gender equality in a changing world: Taking stock and moving forward. OECD Publishing. https://doi.org/10.1787/e808086f-en

Organisation for Economic Co-operation and Development (OECD). (2025b). OECD Skills Outlook 2025: Building the skills of the 21st century for all. OECD Publishing. https://doi.org/10.1787/26163cd3-en

Rani, U., Gobel, N., & Uludag, S. (2026). Unmasking gender disparities in the digital economy: Beyond access and numbers. In J. Rubery, N. Sánchez-Mira, & V. Insarauto (Eds.), Women in turbulent times: Crises, transitions and challenges for gender equality (pp. 275–296). Routledge. https://doi.org/10.4324/9781003528210-17

Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, L 2024/1689, 12 July 2024. https://eur-lex.europa.eu/eli/reg/2024/1689/oj

Regulation (EU) 2026/1744 of the European Parliament and of the Council of 8 July 2026 amending Regulations (EU) 2024/1689, (EU) 2018/1139 and (EU) 2023/1230 as regards the simplification of the implementation of harmonised rules on artificial intelligence (Digital Omnibus on AI), OJ L, 2026/1744, 24.7.2026.

Reskin, B. F. (1993). Sex segregation in the workplace. Annual Review of Sociology, 19, 241–270. https://doi.org/10.1146/annurev.so.19.080193.001325

Ricaurte, P. (2024, February 1). How can feminism inform AI governance in practice? UNESCO Global AI Ethics and Governance Observatory.

Robbenhaar, M., Dinale, D., Breitkreuz, R., & Baird, M. (2026). What is women's 'economic' empowerment? Meanings and measurement. In R. Breitkreuz & M. Baird (Eds.), Women's economic empowerment and the state: A critical human ecological approach (pp. 30–47). Edward Elgar Publishing.

Showalter, K. (2016). Women's employment and domestic violence: A review of the literature. Aggression and Violent Behavior, 31, 37–47. https://doi.org/10.1016/j.avb.2016.06.017

Stöckl, H., Hassan, A., Ranganathan, M., & Hatcher, A. M. (2021). Economic empowerment and intimate partner violence: A secondary data analysis of the cross-sectional Demographic Health Surveys in Sub-Saharan Africa. BMC Women's Health, 21, Article 241. https://doi.org/10.1186/s12905-021-01363-9

Tang, C., Li, S. K., Hu, S., Zeng, F., & Du, Q. (2025). Gender disparities in the impact of generative artificial intelligence: Evidence from academia. PNAS Nexus, 4(2), pgae591. https://doi.org/10.1093/pnasnexus/pgae591

UN Women. (2023). Addressing violence against women through social protection: A review of the evidence. https://knowledge.unwomen.org/en/digital-library/publications/2023/03/policy-brief-addressing-violence-against-women-through-social-protection

UN Women. (2024, June 28). FAQs: Economic empowerment.

UN Women, & United Nations Department of Economic and Social Affairs. (2025). Progress on the Sustainable Development Goals: The gender snapshot 2025. United Nations.

UNESCO. (2024). Women for Ethical AI: Outlook study on artificial intelligence and gender. UNESCO.

UNESCO. (2025, August 4). Closing the digital divide for women and girls in Africa through education.

UNESCO. (2026). Outlook Study on Artificial Intelligence and Gender in South Asia. UNESCO Regional Office for South Asia.

UNESCO. (2026, February 6). Advancing gender equality in STEM education: Inspiring girls to pursue science. https://www.unesco.org/en/articles/advancing-gender-equality-stem-education-inspiring-girls-pursue-science

UNESCO. (n.d.). Women4Ethical AI. Retrieved September 15, 2026, from https://www.unesco.org/en/artificial-intelligence/women4ethical-ai

United Nations Economic Commission for Europe. (2025). Improving artificial intelligence standards for an equitable future (ECE/TRADE/495). United Nations.

United Nations Educational, Scientific and Cultural Organization (UNESCO). (2021). Recommendation on the Ethics of Artificial Intelligence. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000381137

United Nations Educational, Scientific and Cultural Organization (UNESCO). (2026). Legal Dimension. Global AI Ethics and Governance Observatory. https://www.unesco.org/ethics-ai/en/node/343

United Nations Educational, Scientific and Cultural Organization. (2021). Women and the digital revolution. In UNESCO science report: The race against time for smarter development. UNESCO.

Wajcman, J. (2004). TechnoFeminism. Polity.

World Economic Forum. (2026). Global Gender Gap Report 2026. World Economic Forum.

World Health Organization. (2026, June 18). Violence against women. https://www.who.int/news-room/fact-sheets/detail/violence-against-women

Wright, L., Muenster, R. M., Vecchione, B., Qu, T., Cai, P. S., Smith, A., COMM/INFO 2450 Student Investigators, Metcalf, J., & Matias, J. N. (2024). Null compliance: NYC Local Law 144 and the challenges of algorithm accountability. In Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency (pp. 1701-1712). Association for Computing Machinery. https://doi.org/10.1145/3630106.3658998

Wängnerud, L. (2009). Women in parliaments: Descriptive and substantive representation. Annual Review of Political Science, 12, 51–69. https://doi.org/10.1146/annurev.polisci.11.053106.123839