Journal of Business and Digital Innovation (JBDI)
Volume 1, Issue 2, July 2026, PP 33-49
ISSN 2978-4522 (Print) & ISSN 2978-4530 (Online)
https://doi.org/10.19164/jbdi.v1i2.1850

Tripartite Accountability in AI-Driven Workforce Displacement: A Stakeholder and Legal Perspective

[1]Tobi Nwulu, & [2]Omoseni O. Adepoju

[1]Alliant International University, California, USA
[2]Lead City University, Ibadan, Nigeria

Abstract

Artificial intelligence is restructuring labour markets at a pace that outstrips institutions' capacity to respond, creating a responsibility vacuum in which displaced workers bear the greatest burden of change while retaining the least power to negotiate its terms. This paper examines the allocation of responsibilities for handling AI-driven workforce displacement among employers, workers, and governments, drawing on research from four economies: the United States, Germany, Japan, and Singapore. The Stakeholder and Human Capital Theories are utilised in this paper to analyse the allocation of responsibilities, thereby supporting the central argument that no single actor can adequately address AI-driven displacement alone. The most theoretically grounded and practically viable approach is a tripartite accountability framework in which employers, workers, and governments discharge coordinated, simultaneous obligations. The analysis utilised a narrative review of peer-reviewed literature, policy documents, and institutional reports published between 2020 and 2026. Findings show that employers bear proactive obligations that extend beyond legal compliance, as workers are responsible for adapting their skills and engaging in collective advocacy, and that governments must close the gap between the pace of AI adoption and the adequacy of regulatory and labour market policy responses. This paper contributes a structured tripartite accountability framework to the growing literature on AI governance and workforce management, with practical implications for employers, policymakers, and worker organisations that are navigating AI-driven labour market transitions.

Keywords: AI displacement, tripartite accountability, workforce governance, stakeholder theory, reskilling

Wordcount: 224

1.0 Introduction

Artificial Intelligence (AI) has made significant progress in the Fourth Industrial Revolution, driven by vast amounts of data, improved computing power, and more efficient learning algorithms. Although the development of AI dates to the middle of the 20th century, its applications have accelerated significantly in recent years. AI is described as a sub-discipline of computer science dedicated to developing data-processing systems and executing functions that mimic human intelligence, such as learning, reasoning, and self-improvement (Peres et al., 2020). Historically, technological advancements have often led to shifts in employment patterns, with certain job roles becoming automated or obsolete and new opportunities emerging, and generative AI is foreseen to lead to similar fundamental shifts in the labour market, displacing or augmenting exposed roles and creating new skill demands (Karangutkar, 2023; Ledingham, 2025; Chin et al., 2025; Budhwar et al., 2022; Chen et al., 2024).

It is important to explain what 'workforce displacement' means in this paper, since the term is used loosely across the literature. Acemoglu and Restrepo (2019) differentiate displacement, in which AI directly substitutes for tasks previously performed by workers, from reinstatement, in which new tasks and job categories are created for human workers as a result of the same technology. Displacement is therefore not the same as net job loss: an occupation can lose specific tasks to AI while the underlying job survives in altered form, and an economy can experience heavy task-level displacement alongside net employment growth, as the evidence in Section 4 shows. What differentiates AI-driven displacement from earlier waves of automation is its reach into cognitive and administrative tasks previously seen as resistant to substitution,

and the pace of task-level change relative to the institutional capacity to manage it. This paper is concerned specifically with that governance gap, rather than forecasting the effect of AI-Driven Workforce Displacement on employment. Workers are responsible for adapting their skills and workflows to leverage these new AI capabilities, and new technologies create new needs, industries, and complex tasks that need human skills (WEF, 2025). Conversely, it is crucial to assess the potential consequences of AI-driven job displacement on workers, businesses, and society (Karangutkar, 2023).

Despite the scale and pace of AI-driven labour market transformation, there is no clear, empirically validated framework for allocating responsibilities among employers, workers, and governments when AI displaces workers. The absence of this framework is not happenstance. A recent review of 245 global AI ethics guidelines determined that where labour-related disruptions appeared in those frameworks, there was no enforceable standards or institutional mechanisms for allocating responsibilities and subsequent implementation and monitoring (Cabiddu et al., 2025). The acceleration of AI adoption has consistently outpaced the institutional frameworks, generating what this paper terms a responsibility vacuum. Recent guidance directed at corporate boards argues that workforce impact has, in practice, been left as everybody's responsibility, which means nobody's in particular (Renieris et al., 2026). This responsibility vacuum has been left unaddressed, consequently producing avoidable suffering, wasted human capital, since the earnings losses associated with job displacement are large and persist for years, and growing social inequality, since the benefits of AI adoption accrue disproportionately to already high-income groups and the outcomes are neither economically efficient nor ethically justifiable (Davis and von Wachter, 2011; Cazzaniga et al., 2024).

This paper aims to establish how responsibility for managing AI-driven workforce displacement should be allocated among employers, workers, and governments, and to propose a framework to guide that allocation in practice. Three questions are asked: first, what obligations does each of the three actor groups hold toward managing AI-driven displacement, and on what theoretical basis; second, how do these obligations differ in practice across contrasting institutional contexts; and third, what conditions make coordinated tripartite governance more durable than voluntary, employer-led, or state-led alternatives. These questions are pertinent to addressing the consequences of the responsibility vacuum described above, which is already producing consequences such as: workers left without transition support, employers facing reputational and regulatory exposure, and governments improvising policy after the fact. A clearer allocation of obligations could help prevent the consequences of the responsibility vacuum rather than waiting for more complete empirical data.

The remaining sections of this paper are as follows: Section 2 discusses the theoretical framework; Section 3 describes the methodological approach adopted in the paper; and Section 4 analyses the level and nature of AI-driven displacement globally, and particularly in the four focal economies. Section 5 presents the findings across the four thematic areas: employer responsibilities, worker obligations, government interventions, and the tripartite accountability framework. Section 6 interprets the findings against the theoretical framework and the existing literature, while Section 7 concludes, offers practical recommendations, and provides suggestions for future research.

2.0 Theoretical Framework

The analytical approach adopted in this paper is informed by two complementary theoretical frameworks: Stakeholder Theory and Human Capital Theory. These two frameworks provide the conceptual building blocks for the tripartite accountability model established in Section 5.4.

2.1 Stakeholder Theory

The Stakeholder Theory, first formulated by Freeman (1984) and extensively elaborated in management literature, suggests that organisations are responsible not only to shareholders but also to all parties who are interested in or affected by organisational decisions. According to Parmar et al. (2010), effective stakeholder management requires firms to identify and address the legitimate concerns of all stakeholders, rather than focusing solely on those with formal contractual relationships with the organisation. Stakeholder Theory offers a normative ground for allocating responsibility among employers, workers, and the state in the context of AI-driven workforce displacement. Employers, as the primary agents determining AI adoption, bear an obligation towards their worker-stakeholders not only to avoid harm but to actively engage workers throughout the transitions that AI integration introduces. This is supported by De Stefano

and Doellgast (2023), who demonstrate that worker representatives, as intermediaries between employees and employers during AI adoption, must be recognised as legitimate stakeholders.

Workers as stakeholders also carry their own responsibilities, including meaningful participation in retraining programmes, engagement in collective advocacy, and proactive adaptation of their skills in response to technological change. Within a stakeholder model, De Stefano and Taes (2023) document that workers should be active participants capable of exercising rights to education, transition assistance, and collective voice. The third group of stakeholders, governments, must establish enabling environments comprising social safety nets, active labour market policies, and regulatory frameworks that ensure fairness and transparency in AI-driven employment decisions (Eurofound, 2025). This tripartite model of AI displacement management is fundamentally aligned with Stakeholder Theory: it recognises that all three groups are mutually interdependent, with interests that must be balanced and responsibilities that must be discharged simultaneously (De Stefano and Doellgast, 2023).

2.2 Human Capital Theory

The Human Capital Theory, rooted in the foundational work of Becker (1964) and developed further by economists including Mincer (1974) and Schultz (1961), holds that investment in human resources, education, training, and skills development yields returns to individuals, organisations, and society. This theory provides an accessible and analytically powerful framework for understanding AI-driven workforce displacement. As AI alters skill requirements, the capacity to sustain effective education and retraining programmes becomes the central mechanism enabling the workforce to respond. Poghosyan et al. (2026) confirm that effective reskilling strategies reflect the premise of Human Capital Theory, which emphasises that skill development is a long-term, progressive process requiring sustained investment.

For employers, Human Capital Theory implies a direct organisational interest in reskilling. Morandini et al. (2023) reinforce this, arguing that organisations must adopt a proactive approach that maps the transversal skills needed to address current skill gaps and implement targeted training processes to support effective AI adoption. For employees, Human Capital Theory emphasises personal responsibility in continuous learning and skill acquisition. Ersanli et al. (2025) argue that most workers will need foundational AI literacy and the ability to communicate with and work alongside AI systems. For governments, Human Capital Theory provides the strongest justification for active labour market policies. Because private markets systematically under-invest in general training, employers fear losing retrained workers to competitors. Government co-investment is the only mechanism capable of achieving socially optimal levels of human capital formation (Becker, 1964; Schultz, 1961).

2.3 Towards a Tripartite Accountability Framework

The Stakeholder Theory and the Human Capital Theory each address different aspects of AI-driven workforce displacement. Stakeholder Theory focuses on distributed responsibility: employers, workers, and governments each hold genuine claims to the governance of AI adoption, and each has obligations that cannot be reduced to those of the others. Human Capital Theory discusses coordinated investment and argues that displacement is a market failure in human capital formation that private actors alone cannot structurally correct.

Read together, the two frameworks reach the same conclusion. Responsible AI governance entails synchronised and harmonised action across all three actor groups, and this harmonisation is what the paper terms tripartite accountability. This is a framework that ensures employers invest proactively in workforce transition, workers take action through reskilling and collective advocacy, and governments create enabling regulatory and policy. It is a concept with deep institutional roots in the International Labour Organization (ILO) governance model, which has structured relations between governments, employers, and workers in international labour standard-setting since 1919 (ILO, 2024).

3.0 Methodology

This paper addresses the research questions set out in Section 1 through a theoretically driven narrative review methodology (Snyder, 2019). A narrative review was chosen rather than a systematic or scoping review, because the objective of the paper is to construct a theoretical argument from a defined body of literature and test that argument against institutional evidence from four countries. Grant and Booth (2009) identify this as a distinct and legitimate review type which is suited to research questions that are conceptual

and explanatory rather than purely descriptive. As discussed further in Section 7.2, a narrative review does not offer the exhaustive coverage or transparent inclusion and exclusion protocol of a systematic approach.

The review is structured into four steps. First, a scoping search used the terms 'artificial intelligence', 'workforce displacement', 'job automation', 'employer responsibility', 'reskilling', 'labour market policy', and 'tripartite governance', in combination, across Google Scholar, ScienceDirect, and the institutional repositories of the OECD, IMF, World Economic Forum, and Eurofound. Second, records were screened for relevance to the three research questions and for direct engagement with a focal economy or with employer, worker, or government responsibilities specifically; general AI-adoption studies without a labour market or governance dimension were excluded. Third, retained sources were appraised for credibility, prioritising peer-reviewed articles and reports from established international institutions over grey literature. Grey literature was kept where it offered the most current evidence, since institutional reports in this field frequently preceded peer-reviewed publication by a year or more. Fourth, sources were synthesised thematically around the four results areas in Section 5, cross-referenced against the theoretical categories in Section 2.

Sources were drawn predominantly from material published between 2020 and 2026, showing the period in which generative AI moved from the research phase to widespread workplace deployment. Foundational theoretical works (Freeman, 1984; Becker, 1964; Mincer, 1974; Schultz, 1961) were included irrespective of publication date, given their continuing relevance to the theoretical framework in Section 2. Table 1 gives an indicative breakdown of the reference base by source type and period. Table 2 gives indicative examples of the material retrieved from the main institutional repositories consulted.

Table 1.
Indicative composition of the reference base by source type and publication period (n = 56 cited sources).

Source type	Pre-2020	2020-2022	2023-2024	2025-2026	Total
Peer-reviewed journal articles		5	8	11	24
Institutional reports (OECD, IMF, WEF, Eurofound, ILO, IISD, and similar)		3	9	11	23
Policy briefs, think-tank publications, and preprints		3	0	2	5
Foundational theoretical works (pre-2020)	4	-	-	-	4
Total		11	17	24	56

Table 2.
Indicative examples of material retrieved from each institutional repository consulted.

Repository	Example sources retrieved and used in this paper
OECD	OECD (2023) Employment Outlook: AI and the labour market; OECD (2024) Employment Outlook; OECD (2025a) Bridging the AI skills gap; OECD (2025b) AI and the labour market in Japan
IMF	Cazzaniga et al. (2024) Gen-AI: Artificial Intelligence and the Future of Work; Jaumotte et al. (2026) Bridging skill gaps for the future
World Economic Forum	WEF (2025) Future of Jobs Report 2025; WEF (2026) Four Futures for Jobs in the New Economy
Eurofound	Eurofound (2025) Collective bargaining on artificial intelligence at work

Priority was given throughout to cross-national comparative studies and to empirical analyses specific to the four focal economies, which are consistent with the paper's comparative institutional design.

4.0 AI-Driven workplace displacement: Scale and context

The scale and pace of AI-driven workforce displacement cannot be adequately understood through theoretical argument alone. Empirical evidence from global labour market studies, sector-specific analyses, and cross-national comparisons is necessary to establish the context within which the tripartite accountability framework operates. Evidence for this section was compiled from the same source pool described in Section 3.0. Priority is given to the most recent global institutional reports for cross-national comparability, augmented with the peer-reviewed sectoral and country-specific studies identified through the same database searches. This section documents the global evidence of displacement, examines sectoral

vulnerability across manufacturing, healthcare, and transportation, and situates these trends within the four focal economies.

4.1 Global evidence of displacement

Whilst there is no consensus on the scale of AI-driven displacement in numerical terms, there is broad agreement that net employment effects are not as far-reaching as expected. Around 40% of global employment is exposed to AI (Cazzaniga et al., 2024), with clerical, legal, and engineering tasks facing the highest disruption (Goldman Sachs, 2023). The effect operates mainly at the task level rather than across entire occupations, and the IMF estimates that 85 million jobs will be displaced globally, compared with 97 million newly created, a modest net gain that masks substantial occupational restructuring (Cazzaniga et al., 2024). Higher AI exposure is nonetheless associated with reduced employment and shorter working hours (Dominski and Lee, 2025), and roughly a quarter of jobs sit in the highest-risk automation category, with three in five workers worrying about losing their jobs within a decade (OECD, 2024). 63% of workers, however, report that AI has improved their enjoyment of work by removing tedious tasks (OECD, 2024), emphasizing that the governance challenge is managing an uneven transition rather than reversing an unavoidable decline.

4.2 Sectoral Vulnerability

4.2.1. Job displacement in the manufacturing sector

In manufacturing, the question of whether AI leads to machine replacement or job creation remains one of the most pressing concerns in contemporary labour economics (Huo et al., 2024). AI is applied across many production processes, including product development, production and packaging, quality control, and logistics and distribution. Displacement operates through two mechanisms: the direct substitution effect, manifested in automated production-line robots replacing traditional, manual labour, and the indirect substitution effect, whereby the introduction of intelligent equipment increases the unit productivity of the product while reducing labour demand (Huo et al., 2024). Vulnerability to displacement is deeply stratified by skill: low-skilled labour is more likely to be replaced, and the employment quality of low-skilled migrant workers is more severely affected by industrial intelligence (Huo et al., 2024). Temporally, the substitution effect dominates in the short term, and the current development of AI in China remains dominated by the substitution effect on manufacturing labour employment (Huo et al., 2024).

4.2.2 Job displacement in the health sector

Healthcare is undergoing a significant transformation driven by the rapid advancement of AI. This has raised numerous concerns among the healthcare workforce, including job security, ethical considerations, and its impact on the patient-provider relationship, as workers fear losing their jobs to AI taking over routine tasks (Rony et al., 2024). The fear of unemployment, coupled with the anxiety of acquiring new skills, can be profoundly distressing for those who have dedicated their lives to the medical profession, further compounded by concerns about accountability and responsibility associated with AI errors (Rony et al., 2024).

4.2.3. Job displacement in the transportation Sector

The transportation industry will be among the first to experience the aftermath of autonomous vehicles, as these can eliminate driving professions and create new layers of employability-related social exclusion (Nikitas et al., 2021). The scale of this threat is substantial, with Frey and Osborne (2017) estimating that around 47% of total US employment will be in the high-risk category over the next two decades due to computerisation, including jobs in the transport and logistics industry (Nikitas et al., 2021). Vulnerability is concentrated among drivers of buses, taxis, and trucks, who earn above the minimum wage and require no college degree; motor vehicle operators also tend to be older and less educated, with more limited transferable skills than other employees (Nikitas et al., 2021).

4.3 Displacement Across Four Economies

The next subsections will examine the four focal economies that will be used throughout this paper. These focal economies were selected because they represent different institutional contexts within the varieties-of-capitalism framework (Hall and Soskice, 2001): the USA is a Liberal Market Economy in which labour market coordination is largely left to firms and markets; Germany is a Coordinated Market Economy, structured through statutory works councils and sectoral bargaining; Japan combines enterprise-based employment security with limited external labour market coordination; and Singapore operates a state-

directed tripartite structure involving government, employers, and trade unions. This selection is not representative of the full range of national responses to AI-driven displacement, but it provides meaningful institutional contrast for examining how governance architecture shapes tripartite outcomes. The limitation is further discussed in Section 7.2.

4.3.1 United States of America

A study by the OECD (2023) reveals that approximately 27% of jobs across OECD countries face a high risk of significant transformation due to artificial intelligence automation within the next five years. The OECD (2023) further highlights that highly skilled occupations in finance, medicine, and the legal sector, which traditionally require extensive education and accumulated experience, now face a substantial risk of automation. Across law firms, financial institutions, and healthcare facilities, AI tools produce outputs virtually, which cannot be distinguished from human work, placing these professionals squarely within AI's reach for potential transformation.

4.3.2 Germany

In Germany, AI dominates debates on the digitalisation of work, with significant focus on its role in job substitution (Giering and Kirchner, 2025). Approximately 38% of workers used at least one AI-based system, with 28% using AI to recognise and interpret data and 21% for text recognition and processing. Adoption of AI is heavily skewed by skill level: 56% of higher-grade managers and professionals reported using AI compared to only 18% of unskilled and semi-skilled workers. The effects are particularly strong for unskilled and semi-skilled workers at -22.4 %, agricultural labourers at -25.3 %, and lower-grade routine non-manual workers at -15.3 %, confirming that digitalisation benefits those with higher skills and autonomy while automating low-skilled and routine tasks, a pattern echoed across the EU more broadly, where occupational polarisation is more prevalent among workers without university degrees and varies sharply by geography (Brekelmans and Petropoulos, 2020). With AI technology continuing to evolve, future displacement is expected to worsen as an increasing number of tasks are performed by AI (Giering and Kirchner, 2025).

4.3.3 Japan

Japan has the lowest AI adoption rate among countries surveyed. Only 8.4% of employees use AI at work in Japan, and 6.4% use generative AI, representing a 35.7 percentage-point difference from the United States in finance and insurance and a 34.1 percentage-point difference from Ireland in manufacturing (OECD, 2025b). Currently, only 4.3% of workers report knowing someone who has lost their job due to AI, with 12.9% in finance and insurance and 15.0% in manufacturing reporting this. However, concerns about future displacement are significantly greater: 73.8% of Japanese AI users in finance and insurance worry about job loss over the next ten years compared to 68.0% in other countries, while in manufacturing the equivalent shares are 71.3% in Japan versus 65.8% in other countries (OECD, 2025b). Displacement risk is highly unequal across occupational groups. Among low-income groups and non-regular employment, worries about job loss outweigh expectations for job creation. With 89.4% of AI users expecting the skills required in their current job to change over the next ten years, and a 13.5 %-point difference between occupations with the highest and lowest AI use, even as outright displacement remains currently limited due to Japan's unique long-term employment system and chronic labour shortages (OECD, 2025b).

4.3.4 Singapore

According to Cazzaniga et al. (2024), about 77% of Singapore's employed workers are highly exposed to AI, surpassing the average high-exposure rates of 40% for emerging market economies, 26% for low-income countries, and even exceeding the 60% estimated for advanced economies. Within this highly exposed group, about half are in occupations with high AI complementarity (38.9%), while the other half are in occupations with low AI complementarity (38.6%). Gender and age disparities are stark: 49% of female workers are in occupations with high exposure and low complementarity, compared to 29% of male workers, while half of younger workers face high AI exposure and low complementarity, with only one-fifth in high-exposure, high-complementarity occupations. Singapore's robotic intensity further compounds displacement risk, with 730 industrial robots per 10,000 employees and an average annual increase of 27% since 2015. The vulnerability of lower-skilled workers is evidenced by pandemic-era data: 181,500 foreigners lost their jobs, far exceeding the number of job losses during prior financial crises, with low-skilled workers accounting for 76% of those job losses.

5.0 Results

The narrative review identified four interconnected thematic findings concerning the allocation of responsibilities for AI-driven workforce displacement among employers, workers, and governments. Each theme is examined in turn, with reference to the theoretical frameworks established in Section 2 and the contextual evidence presented in Section 4.

5.1 Employer Responsibilities in Managing AI-Driven Workforce Displacement

The implementation of AI by employers has completely changed the face of the modern-day workplace in terms of its organisation. In companies that incorporate AI technologies, employer reactions range from actively investing in worker retraining to transition assistance. Acemoglu and Restrepo (2020), in research on US labour markets, found that AI-driven institutions are more likely to reduce total staffing, meaning that AI-driven productivity gains are not necessarily converted into net employment gains.

There are three general strategic responses that employers have sought when adopting AI. Investment in upskilling and reskilling to retrain current employees, as the National Academies of Sciences, Engineering, and Medicine (NASEM, 2025) describe retooled jobs that retain job title but change in internal skills as a result of AI. NASEM (2025) finds that AI has the potential to augment human labour and create new forms of valuable work, but only if institutional actors, especially employers, adopt it responsibly.

Secondly, employers undergo workforce restructuring without any transition assistance. Based on a survey of more than 1,000 employees representing 14 million employees across 55 economies, the report finds that 41% of employers expect their workforce to downsize by 2030 as AI automates some of their functions (WEF, 2025). This highlights the dominance of displacement-based responses, even in large, internationally advanced companies. Third, there is a more subtle reaction: partial automation, in which only some tasks are automated, and workers are reallocated to other jobs that complement their original roles. In the WEF (2025) report, nearly half of the employers surveyed anticipate shifting employees experiencing the effects of AI disruption into other areas of their operations, indicating that jobs will not be lost but will be redefined as entirely different.

Sharfuddin (2025) claims that, in response to AI-induced job displacement, upskilling offered by companies will allow employees to move to less automated positions, thereby sustaining their employment and further enhancing their earnings. Employer upskilling intervention does not only serve as a social responsibility but also as an economic rationale consistent with Human Capital Theory.

In Germany, the employer's roles are institutionalised by the Works Constitution Act, which requires consultation with works councils when introducing major technological change. The EU AI Act, which became effective in August 2024, categorises human resource management as a high-risk domain and establishes transparency and accountability requirements for AI systems used in employment decision-making. Malin et al. (2025) indicate that regulation has increased the responsibilities of employers, finding that worker representatives require regulations and well-defined responsibilities as conditions for accepting AI in the workplace. Historically, in Japan, technological adoption has been handled through robust enterprise-level investment in lifetime employment and internal redeployment, but with the increasing automation of AI in manufacturing industries.

Employers in Singapore operate within a system of shared responsibility through the Skills Future programme adopted by the government. According to the OECD (2025a) analysis of AI skills training across Australia, Germany, Singapore, and the United States, Singapore has one of the most practical workforce transformation policy responses to AI, and companies can obtain significant government co-financing to train their workforce. The OECD (2025a) cross-national analysis further notes that most AI-related training is currently focused on professionals with advanced qualifications to ensure wide workforce participation in AI literacy.

Employer-related requirements in the context of workforce reduction are increasingly being scrutinised in the US through the lens of AI transparency. Employees can also use collective bargaining to control the conditions under which AI is implemented in their jobs, as was the case with the Writers Guild of America and SAG-AFTRA agreements in 2023, which established contractual rights regulating the use of AI and explicitly moved the burden of negotiating proper transitioning conditions to employers (Kelley, 2024).

Moreover Eurofound (2025) posits that employers operating within European frameworks are being increasingly expected to negotiate AI governance terms, including requirements of transparency, guarantees of job security, and commitments to retraining as conditions of AI implementation. Overall, the role of the employer in AI-driven workforce displacement goes far beyond legal requirements but includes investment in upskilling and accountability at the governance level for the human impact of AI implementation.

From a legal point of view, the obligations identified are grey areas that fall between ethical expectation and legal requirements. Majority of employer responsibilities that are identified in this review are in the domain of soft law, that is, voluntary codes, negotiated agreements, and executive guidance that individual employers may observe selectively and governments may reverse without legislative process. The legal framework regulating employer conduct in AI-driven displacement does not reflect the scale of the problem, and closing this gap will entail legislative intervention beyond collective bargaining (Kelley, 2024; Malin et al., 2025).

5.2 Worker Obligations and Agency

5.2.1 Effects of Displacement on Workers: Economic, Psychological, and Social Dimensions

Economically, displaced workers lose income, face extended periods of unemployment, and struggle to re-enter similar roles, particularly older and low-skilled workers. Cazzaniga et al. (2024) provide strong evidence of age-related vulnerability: older workers are less likely to re-employ in the same type of occupation after displacement than prime-age workers. This observation aligns with World Economic Forum (2025), showing that by 2030, 92 million jobs will be eliminated, starting with workers in routine administrative and clerical functions, categories where women and older people are over-represented.

Acemoglu and Restrepo (2020) provide empirical data on US labour markets, showing that every additional robot per thousand workers lowers the employment-to-population ratio by 0.2 percentage points and wages by 0.42%, with impacts concentrated in local labour markets greatly affected by automation. Cazzaniga et al. (2024) further claims that AI will simultaneously alter the career patterns of more skilled employees, strengthening trends of economic inequality across skill levels. Specifically, the IMF analysis states that labour income inequality can rise where the complementarity between AI and high-income employees is high, and that capital rewards will widen wealth inequality.

The psychological implications of AI-induced displacement are no less significant. Sharma et al. (2025) identified six specific psychological themes among AI-displaced workers, including emotional shock, loss of professional identity, persistent anxiety and anticipatory rumination, social withdrawal, and adaptive and maladaptive coping. They found that job displacement caused by technology produces greater psychological distress than displacement caused by traditional layoffs.

It is worth noting that the picture is not entirely negative. In a longitudinal study based on the German Socio-Economic Panel data between 2000 and 2020, Giuntella, Konig, and Stella (2025) did not find evidence of large negative effects of AI on workers' well-being and mental health in the German context and identified indications of improved health satisfaction. The authors attribute this to the institutional environment in Germany, characterised by high labour protection standards, the presence of unions, and broad employment laws that make AI more likely to complement rather than substitute worker skills. The comparison between the German and Indian IT sector findings underscores the significance of national frameworks and specific employer practices in shaping worker outcomes.

5.2.2 Worker Obligations in the Context of AI-Driven Displacement

Although much of the literature on displacement focuses on what employers and governments must do, a growing body of evidence identifies a range of responsibilities that workers themselves must undertake in managing the changes introduced by AI. According to the UC Berkeley Labor Center (2024), employees have both a right and a duty to organise and negotiate regarding the application of AI technologies by employers. The centre promotes the right of workers to receive education and training to expand their skills when tasks are automated, the right to be offered job opportunities ahead of external candidates in the event of redeployment, and protection against job loss due to technology adoption in the event of a layoff. The IndustriAll Europe (2023) further argues that employees and trade union representatives are best positioned to understand the actual impacts of AI technologies at work. In this respect, employees have a

proactive role in engaging in social discourse, bargain for satisfactory training opportunities, revise health and safety standards, and provide feedback on technologies that are not operating fairly.

At the individual level, the Center for American Progress (2024) insists that employees should make efforts to build their own adaptability. The OECD (2025a) policy brief on bridging the AI skills gap concludes that the majority of workers who will be interacting with AI will not need to possess specialised AI skills, but rather a general AI literacy, an awareness of how to communicate and cooperate with AI systems, making self-directed learning a realistic and necessary worker requirement. This finding holds across the four countries examined, Australia, Germany, Singapore, and the United States, and supports the view that worker agency in managing AI displacement can be exercised through modular upskilling accessible within employer-led training programmes.

5.2.3 Heterogeneity in Worker Vulnerability and Agency

The obligations described in 5.2.1 and 5.2.2 assume that a worker has the time, resources, and institutional support needed to reskill. However, that assumption does not hold equally across the workforce. The evidence already presented in this paper shows that being vulnerable to displacement and the capacity to respond to it, is tied to age, gender, skill level, and employment status and is not distributed evenly. For instance, older workers are less likely to re-employ in their original occupation after displacement than prime-age workers (Cazzaniga et al., 2024). In Singapore, women are more likely than men to be in the low-complementarity segment of the labour market where AI is most likely to substitute rather than augment their work (Cazzaniga et al., 2024). Low-skilled workers accounted for most pandemic-era job losses among the country's foreign workforce (Cazzaniga et al., 2024). In Germany, the same skill gradient appears in reverse: AI use is concentrated among higher-grade managers and professionals, while unskilled and semi-skilled workers face the steepest negative employment effects (Giering and Kirchner, 2025).

These patterns are important to understanding how the worker obligations set out in Section 5.2.2 should be read. Structural constraints facing displaced workers, such as limited transferable skills, caring responsibilities, and reduced geographic mobility, cannot be ascribed to the failures of individual agency, and proactive reskilling is not equally available to a 55-year-old routine clerical worker and a 30-year-old professional whose employer already funds AI training. This is exactly where the obligations of employers and governments described in Sections 5.1 and 5.3 become necessary under Human Capital Theory: private markets under-invest in training for exactly the workers least able to self-fund it, which is why government co-investment and employer-led modular training matter most for older, lower-skilled, and non-regular workers rather than the workforce as a whole.

5.3 Government Interventions and Policy Frameworks

Governments play a central role in addressing the labour market impacts of AI-driven displacement. Their tools include regulatory frameworks, active labour market policies, social protection systems, and the coordination of multi-stakeholder responses. Among the most urgent regulatory issues is the lack of disclosure requirements regarding whether workforce reductions or recruitment freezes are connected to AI implementation, a gap that only governmental involvement can adequately resolve (Kelley, 2024). The 2023 Executive Order on the Safe, Secure, and Trustworthy Development and Use of AI represented a regulatory intervention in the US, instructing the US Department of Labour to assess the capacity of agencies to assist workers who lose their jobs due to AI, and identifying workplace surveillance, bias, and job elimination as dangers to be mitigated (Center for American Progress, 2024). In May 2024, one of the mandates published by the Department of Labour prohibited the use of AI systems to undermine workers' rights to organise.

Eurofound (2025) records that the adoption of the EU AI Act prompted government and social partner initiatives across various EU member states to formulate sectoral-level agreements governing the use of AI in employment, including in Germany where a national cross-industry agreement in 2024 modified previous collective agreements to add AI governance roles. The government response to AI-based displacement in Japan has been conditioned by its past reliance on enterprise-based employment security. Japan has implemented AI-related upskilling incentives and digital literacy programmes as part of its Society 5.0 agenda, but their effectiveness appears less broad than the Singapore model. The government of Singapore has developed what the OECD (2025a) considers one of the most coordinated responses to AI-based

workforce transformation, integrating government funding, employer engagement, and modular, worker-accessible training through its SkillsFuture programme.

5.3.1 Active Labour Market Policies, Retraining, and Regulatory Frameworks

The most immediate tools that governments can use to reemploy displaced workers are active labour market policies, encompassing public retraining programmes, wage subsidies, employment counselling, and job placement services. Jacobs (2025) records that the United States is among the OECD countries with the lowest level of active labour market policy spending, at around 0.1% of GDP, a ratio of investment in human capital that is fundamentally inconsistent with the scale of AI-induced displacement documented by the OECD (2025a) and IMF (Cazzaniga et al., 2024). Rather than the generalised support currently offered under the Workforce Innovation and Opportunity Act, the Urban Institute (2025) suggests a more specific policy response in the form of an AI Adjustment Assistance programme, modelled on the Trade Adjustment Assistance paradigm, that includes retraining, income support, job search assistance, and relocation support for workers displaced by AI.

The establishment of regulatory frameworks covering algorithmic transparency in employment decisions is also a major area of government intervention. Eurofound (2025) records how collective bargaining agreements across European nations are being applied to safeguard workers against arbitrary algorithmic decision-making and to guarantee disclosure of AI-influenced staffing decisions. The Corporation for a Skilled Workforce (2025) argues that workforce systems should focus on implementation, integrating AI skills development into existing WIOA and community college systems to better track labour market performance. To meet growing demand for general AI literacy across all four countries, OECD (2025a) policy brief recommends that governments increase non-financial levels, including career guidance, public-corporate partnerships, and train-the-trainer programmes, to deliver AI training to increasingly diverse populations.

Furthermore, a review of the government interventions across the four economies shows a clear difference between binding instruments and policy-based responses. For instance, the EU AI Act and Germany's Works Constitution Act are examples of hard law which are binding, imposing enforceable obligations, and carry penalties for non-compliance. On the other hand, the provisions of the US executive orders on AI cannot be enforced and are reversable by succeeding administrations, revealing the limitations of policy-based responses as against binding instruments (Kelley, 2024; UC Berkeley Labor Center, 2024). Similarly, Japan's Society 5.0 agenda, which relies on government-sponsored upskilling incentives and digital literacy programmes and the Singapore's SkillsFuture framework, reveals the limitations of policy-based responses lacking the statutory grounding that characterises the European approach (OECD, 2025a).

5.4 Towards a Tripartite Accountability Framework

None of the employers, workers, or governments can handle the challenge of AI-driven workforce displacement singlehandedly. An increasing number of researchers support the concept of tripartite and multi-stakeholder models, in which all three stakeholders are given coordinated responsibilities that are performed simultaneously. The World Economic Forum (2025) specifically encourages organisations to align their talent and AI approaches and to engage employees, governments, and other industry players in AI governance, warning that without such approaches, a winner-takes-all dynamic will emerge and negate the democratic regulation of autonomous AI systems. This aligns with the findings of Malin et al. (2025), who record that the role of workers requires not merely technical protection but real involvement in the process of AI implementation in human resource management.

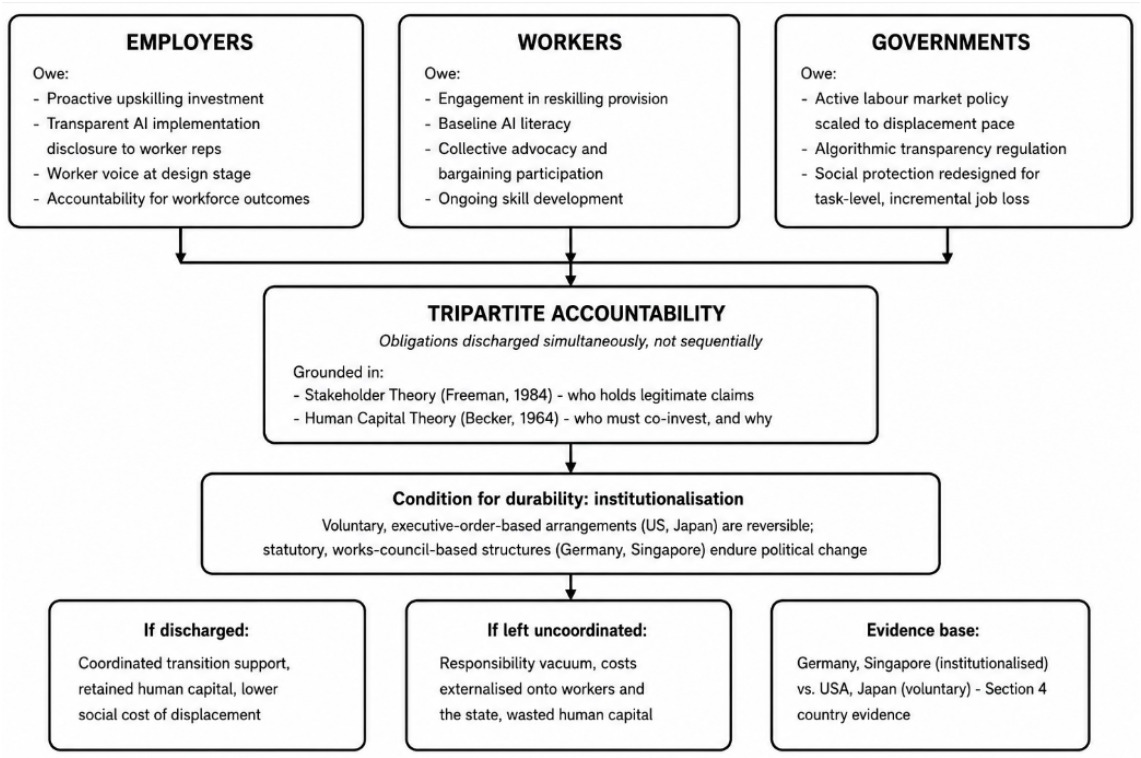

Figure 1. The tripartite accountability framework

Figure 1 sets out the framework's structure, discussed in this section. Employers, workers, and governments each have distinct obligations, by virtue of: their capacity to shape AI deployment, their exposure to its consequences, and their capacity to co-invest in human capital formation that private markets under-provide. These obligations must be discharged simultaneously rather than sequentially, and the evidence below shows that the condition determining whether that coordination holds over time is institutionalisation. The tripartite model has certain institutional manifestations across the four focal economies. In Germany, the Works Constitution Act and institutional social partnerships formally provide opportunities for tripartite consultation on technological change, and collective agreements on AI-related matters (Eurofound, 2025). Eurofound (2025) records that when the EU AI Act came into force in August 2024, government and social partner actions across various European member states, including Germany, saw a 2024 cross-industry agreement revised to establish AI governance functions such as senior AI coordination officers and AI ethics experts.

In Singapore, the tripartite model is institutionalised through the National Trades Union Congress, the Singapore Business Federation, and the government have made it possible to develop policies quickly in a co-design format, including the SkillsFuture programme and sector-based workforce transformation plans. The OECD (2025a) analysis of Singapore's AI training landscape concludes that it is the most systematically financed of the four countries examined, with the government integrating public funding, employer involvement, and modular training trajectories to avoid the social exclusion of displaced employees over the long term. Multi-stakeholder governmental coordination in the United States is less institutionally formalised, yet it is developing through a mix of federal executive action, union collective bargaining, and employer-driven efforts. Kelley (2024) reports that the WGA and SAG-AFTRA agreement of 2023 have served as a template for contractual AI regulation that continues to be replicated in other areas of the labour force. The UC Berkeley Labor Center (2024) also records how the 2023 and 2024 executive orders on AI included provisions encouraging federal agencies to consult with employee unions on the design, development, and use of AI systems, though most of these provisions have since been reversed by successive administrations, reflecting the vulnerability of voluntary multi-stakeholder arrangements to political change and the need to protect them through more durable institutional structures.

Baker McKenzie (2025) records that in 2023, one of the largest technology firms in the world entered into a ground-breaking agreement with a trade union to discuss the effects of AI on employees, including training union members on AI fundamentals, obtaining worker input to inform AI development, and

engaging in lobbying related to AI workforce training policies. The multi-stakeholder imperative is not merely a statement of intention but a structural necessity: none of the actors individually possesses the resources, legitimacy, and reaches to handle AI displacement at the scale and pace at which it is occurring (IISD, 2022; WEF, 2025).

6.0 Discussion

The findings presented in Section 5 demonstrate that AI-driven workforce displacement is neither a purely technological phenomenon nor one that can be adequately governed by any single actor. Examined through Stakeholder Theory, the evidence confirms that employers, workers, and governments each hold legitimate claims on the governance of AI adoption and each bears obligations that are distinct, non-transferable, and mutually reinforcing. Across all four economies, employer responses to AI-driven displacement have been uneven. Some organisations have invested in upskilling and internal redeployment, recognising that retaining human capital generates competitive advantage over the long term. Others have pursued workforce reduction without transition assistance, effectively externalising displacement costs onto workers and the state. The WEF (2025) finds that 41% of employers expect to downsize their workforce by 2030 as AI automates some functions. This is sobering, and it underscores the gap between what employers are currently doing and what Stakeholder Theory would require of them.

This study finding supports the Human Capital Theory argument that active skill investment acts as a protective factor in environments of technological disruption. Also, older workers, low-skilled workers, women, and workers in non-regular employment face compounding disadvantages that proactive reskilling alone cannot address, and this is where government intervention becomes not merely desirable but, in theory, necessary. Section 5.2.3 sets out this heterogeneity in more detail. The findings also point to a sectoral dimension that the tripartite framework must accommodate. Manufacturing displacement operates mainly through direct and indirect substitution of routine physical tasks and affects low-skilled and migrant labour the most (Huo et al., 2024); healthcare displacement is more concentrated in diagnostic and data-processing tasks and is complicated by the accountability questions that arise when AI contributes to clinical decisions (Rony et al., 2024); and transportation displacement is unusually prevalent among older, less-educated workers with limited transferable skills and an unusual reluctance to reskill even where it is offered according to Nikitas et al. (2021). A single, undifferentiated tripartite framework is unlikely to work equally well across these three sectors because manufacturing and transportation displacement call for the redeployment and income-support instruments emphasised in Section 5.3, while healthcare displacement calls for the accountability and governance mechanisms emphasised in Section 5.1, since the central concern there is less job loss than the terms on which AI is allowed to participate in professional judgement. Section 7.1 develops this sectoral distinction into specific recommendations.

The government evidence across the four economies reveals a consistent and troubling pattern. Policy responses have lagged the pace of AI adoption in all four contexts, though to varying degrees. The United States, where active labour market policy spending remains around 0.1% of GDP, is the weakest performer of the four. Singapore's SkillsFuture programme remains the most systematically financed response among the four, reflecting the Human Capital Theory prescription for government co-investment. Germany's institutional social partnership model provides meaningful protection, though it is under increasing stress as AI penetrates higher-skilled occupations. Japan's response remains the most constrained, with Society 5.0 upskilling incentives yet to achieve Singapore's scale and coverage.

The tripartite accountability framework that emerges from this analysis is not simply a descriptive account of what these three actor groups do. It is a normative argument about what they owe. Employers owe proactive investment in workforce transition, transparent communication with affected workers, and accountability for the human consequences of AI implementation decisions. Workers owe meaningful participation in reskilling programmes, engagement in collective advocacy, and a commitment to ongoing skill development, rather than passively receiving employer and government decisions. Governments owe regulatory frameworks that govern algorithmic transparency, active labour market policies scaled to the actual pace of displacement, and social protection systems redesigned for the incremental and task-level nature of AI-driven job loss.

What distinguishes this framework from existing accounts is its insistence on simultaneity. The evidence from Eurofound (2025) on European collective bargaining and from the IISD (2022) on tripartite dialogue

both confirm that the most effective AI governance practices are those in which all three actor groups are engaged in organised and continuous governance processes. Voluntary arrangements are vulnerable to political change, as the partial reversal of the 2023 and 2024 US executive orders on AI illustrates. Institutionalised tripartite structures, of the kind more deeply embedded in Germany and Singapore than in the United States or Japan, appear more durable and more capable of generating the coordinated responses that AI-driven displacement demands.

7.0 Conclusion

This paper sets out to examine how responsibilities for managing AI-driven workforce displacement should be allocated among employers, workers, and governments. Drawing on Stakeholder Theory and Human Capital Theory, and on evidence from the United States, Germany, Japan, and Singapore, the analysis supports a clear conclusion: the responsibility vacuum that currently characterizes AI governance in labour markets is not an inevitable feature of technological change. It is a product of institutional failure, and it is correctable. Correcting this institutional failure will require a deliberate shift from the soft-law instruments currently prevalent in AI governance toward statutory frameworks capable of enforcing tripartite obligations with the same binding force as existing employment and labour law. The tripartite accountability framework proposed in this paper allocates distinct and coordinated obligations to each actor group.

The comparative evidence from the four focal economies is instructive on this point. Singapore's SkillsFuture programme and Germany's institutionalised social partnership model demonstrate that tripartite accountability is not merely theoretically desirable but practically achievable. The comparatively weaker institutional frameworks in the United States and Japan suggest that voluntary arrangements, while valuable, are insufficient substitutes for the kind of structured tripartite governance that makes employer, worker, and government obligations mutually reinforcing rather than sequentially dependent.

7.1 Recommendations

The recommendations given below are organised by sector, by country, for employers, and by government.

(1) For employers in manufacturing, where displacement operates through direct substitution of routine physical tasks, the priority is redeployment of workers on automated lines into machine-monitoring or quality-assurance roles, supported by upskilling.

(2) For employers in healthcare, where the central concern is accountability rather than job volume, the priority is governance: clear protocols make AI-assisted diagnosis subject to clinician sign-off, and frontline clinical staff are involved in AI procurement decisions.

(3) For transportation and logistics, where the workforce is older, less educated, and reluctant to retrain, the priority is transition design, with AI adoption plans communicated to worker representatives before implementation.

(4) For workers and worker organisations, AI literacy should be treated as a baseline skill, and collective bargaining used to secure enforceable AI governance rights of the kind negotiated by the WGA and SAG-AFTRA in 2023. Given the diversity of workers noted earlier, organisations should treat securing employer- and government-funded training access as priority, rather than assuming workers can self-fund it.

(5) For governments, the evidence supports action tailored to each country's institutional starting point rather than a single template.

(i) For the United States, which faces the lowest active labour market policy spending relative to the scale of displacement among the four economies, priority should be given to scaling that investment, coupled with statutory protections that survive changes in administration.

(ii) For Germany, where Works Constitution Act consultation rights do not yet extend to AI-related technological change, priority should be given to extending them.

(iii) For Japan where Society 5.0 upskilling incentives have yet to reach Singapore's scale and coverage, priority should be given to expanding the agenda, modelling Singapore's SkillsFuture approach.

(iv) For Singapore, which is the strongest performer among the four, priority should be given to extending SkillsFuture's co-financing model to its lower-skilled and foreign-worker segments.

7.2 Limitations and Future Research

This paper is subject to the limitations of narrative review methodology, discussed in Section 3.0. The selection of sources, while systematic in intent, is not exhaustive. The four focal economies, though chosen for their contrasting institutional contexts, are not representative of the full range of national responses to AI-driven displacement. However, for future research, studies can be extended to middle- and lower-income countries where AI adoption patterns and institutional capacity differ substantially. The tripartite accountability framework proposed here is theoretically grounded and supported by qualitative, cross-national evidence, but it has not been quantitatively validated. Consequently, future research that combines the institutional and theoretical account developed in this research with quantitative validation and country-level investment modelling is being recommended to strengthen the practical case for tripartite accountability made in this paper.

References

Acemoglu, D. and Restrepo, P. (2019) 'Automation and new tasks: How technology displaces and reinstates labor', *Journal of Economic Perspectives, 33*(2), pp. 3–30. Available at: https://doi.org/10.1257/jep.33.2.3

Acemoglu, D. and Restrepo, P. (2020) 'Robots and jobs: Evidence from US labour markets', *Journal of Political Economy, 128*(6), pp. 2188–2244. Available at: https://doi.org/10.1086/705716

Baker McKenzie (2025) Navigating labour's response to AI. Available at: *https://www.bakermckenzie.com/en/insight/publications/2025/06/navigating-labors-response-to-ai*

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

Brekelmans, S. and Petropoulos, G. (2020) Occupational change, artificial intelligence and the geography of EU labour markets. Bruegel Working Paper. Available at: *https://www.bruegel.org/working-paper/occupational-change-artificial-intelligence-and-geography-eu-labour-markets*

Budhwar, P., Malik, A., De Silva, M.T. and Thevisuthan, P. (2022) 'Artificial intelligence – challenges and opportunities for international HRM: a review and research agenda', *The International Journal of Human Resource Management, 33*(6), pp. 1065–1097. Available at: https://doi.org/10.1080/09585192.2022.2035161

Cabiddu, F., Di Lauro, S., Samaan, D. and Tursunbayeva, A. (2025) 'Governing AI in the world of work: an international review of 245 ethics guidelines'. Preprint, 31 July. Available at: *https://doi.org/10.31234/osf.io/wsjuq_v1*

Cazzaniga, M., Jaumotte, F., Li, L., Lira, G., Panton, A.J., Pizzinelli, C., Rockall, E.J. and Tavares, M.M. (2024) Gen-AI: Artificial intelligence and the future of work. IMF Staff Discussion Note SDN/2024/001. Washington DC: International Monetary Fund. Available at: *https://www.imf.org/en/Publications/Staff-Discussion-Notes/Issues/2024/01/14/Gen-AI-Artificial-Intelligence-and-the-Future-of-Work-542379*

Center for American Progress (2024) Unions give workers a voice over how AI affects their jobs. Available at: *https://www.americanprogress.org/article/unions-give-workers-a-voice-over-how-ai-affects-their-jobs/*

Chen, W.X., Srinivasan, S. and Zakerinia, S. (2024) Displacement or complementarity? The labour market impact of generative AI. *Harvard Business School Working Paper* No. 25-039.

Chin, T., Li, Z., Huang, L. and Li, X. (2025) 'How artificial intelligence promotes new quality productive forces of firms', Technological Forecasting and Social Change, 216, Article 124128. Available at: *https://doi.org/10.1016/j.techfore.2025.124128*

Corporation for a Skilled Workforce (2025) Future-ready states: Building a workforce that's ready for AI.

Davis, S.J. and von Wachter, T. (2011) 'Recessions and the costs of job loss', Brookings Papers on Economic Activity, 42(2), pp. 1–72. Available at: *https://doi.org/10.1353/eca.2011.0016*

De Stefano, V. and Doellgast, V. (2023) 'Introduction to the Transfer special issue. Regulating AI at work: labour relations, automation, and algorithmic management', Transfer: *European Review of Labour Research, 29*(1), pp. 9–20. Available at: https://doi.org/10.1177/10242589231157656

De Stefano, V. and Taes, S. (2023) 'Algorithmic management and collective bargaining', Transfer: *European Review of Labour Research, 29*(1), pp. 21–36. Available at: https://doi.org/10.1177/10242589221141055

Dominski, J. and Lee, Y.S. (2025) Advancing AI capabilities and evolving labor outcomes. arXiv:2507.08244. Available at: *https://arxiv.org/abs/2507.08244*

Ersanli, C.Y., Celik, F., Barjesteh, H., Duran, V. and Manoochehrzadeh, M. (2025) 'A review of global reskilling and upskilling initiatives in the age of AI', AI and Ethics, 5, pp. 5719–5728. Available at: *https://doi.org/10.1007/s43681-025-00767-9*

Eurofound (2025) Collective bargaining on artificial intelligence at work. Available at: *https://www.eurofound.europa.eu/en/publications/all/collective-bargaining-on-artificial-intelligence-at-work*

Freeman, R.E. (1984) *Strategic management: A stakeholder approach*. Boston: Pitman.

Frey, C.B. and Osborne, M.A. (2017) 'The future of employment: How susceptible are jobs to computerisation?', *Technological Forecasting and Social Change, 114*, pp. 254–280. Available at: https://doi.org/10.1016/j.techfore.2016.08.019

Giering, O. and Kirchner, S. (2025) 'Artificial intelligence and autonomy at work: Empirical insights from Germany', *Journal for Labour Market Research, 59*(1), Article 20. Available at: https://doi.org/10.1186/s12651-025-00401-5

Giuntella, O., Konig, J. and Stella, L. (2025) 'Artificial intelligence and the wellbeing of workers', *Scientific Reports, 15*(1), Article 20087. Available at: https://doi.org/10.1038/s41598-025-98241-3

Goldman Sachs (2023) The potentially large effects of artificial intelligence on economic growth. Goldman Sachs Global Investment Research. Available at: *https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent.html*

Grant, M.J. and Booth, A. (2009) 'A typology of reviews: an analysis of 14 review types and associated methodologies', *Health Information & Libraries Journal, 26*(2), pp. 91–108. Available at: https://doi.org/10.1111/j.1471-1842.2009.00848.x

Hall, P.A. and Soskice, D. (eds) (2001) *Varieties of capitalism: The institutional foundations of comparative advantage.* Oxford: Oxford University Press.

Huo, Q., Ruan, J. and Cui, Y. (2024) '"Machine replacement" or "job creation"? How does artificial intelligence impact employment patterns in China's manufacturing industry?', *Frontiers in Artificial Intelligence, 7*, Article 1337264. Available at: https://doi.org/10.3389/frai.2024.1337264

IndustriAll Europe (2023) AI at the workplace: Collective bargaining needed to ensure worker involvement. Available at: *https://news.industriall-europe.eu/Article/924*

International Institute for Sustainable Development (IISD) (2022) What is tripartite dialogue and how can it help combat the climate crisis in a just way? Available at*: https://www.iisd.org/articles/tripartite-dialogue*

International Labour Organization (2024) Social Dialogue Report 2024: Peak-level social dialogue for economic development and social progress. Geneva: International Labour Organization. Available at: *https://www.ilo.org/publications/flagship-reports/social-dialogue-report-2024-peak-level-social-dialogue-economic-development*

Jacobs, J. (2025) AI labor displacement and the limits of worker retraining. Brookings Institution. Available at: *https://www.brookings.edu/articles/ai-labor-displacement-and-the-limits-of-worker-retraining/*

Jaumotte, F., Kim, J., Koll, D., Li, E.Z., Li, L., Melina, G., Song, A. and Tavares, M.M. (2026). *Bridging skill gaps for the future: New jobs creation in the AI age*. IMF Staff Discussion Note SDN/2026/001. Washington DC: International Monetary Fund.

Karangutkar, A.A. (2023) 'The impact of artificial intelligence on job displacement and the future of work', *International Journal of Advanced Research in Science, Communication and Technology, 3*(1), pp. 635–638. Available at: https://doi.org/10.48175/IJARSCT-12096

Kelley, B.J. (2024) 'Belaboring the algorithm: Artificial intelligence and labour unions', *Yale Journal on Regulation Bulletin, 41*, pp. 88–105. Available at: https://www.yalejreg.com/bulletin/belaboring-the-algorithm-artificial-intelligence-and-labor-unions/

Ledingham, A., Hollins, M., Lyon, M., Gillespie, D., Yunis-Guerra, U., Siviter, J., Duncan, D. and Hauser, O.P. (2025) Beyond automation: Redesigning jobs with LLMs to enhance productivity. arXiv:2512.05659. Available at: *https://arxiv.org/abs/2512.05659*

Malin, C., Fleiss, J. and Thalmann, S. (2025) 'Stakeholder-specific adoption of AI in HRM: workers' representatives' perspective on concerns, requirements, and measures', *Frontiers in Artificial Intelligence, 8*, Article 1561322. Available at: https://doi.org/10.3389/frai.2025.1561322

Mincer, J. (1974) *Schooling, experience, and earnings*. New York: National Bureau of Economic Research, distributed by Columbia University Press.

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D. and Pietrantoni, L. (2023) 'The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations', Informing Science: *The International Journal of an Emerging Transdiscipline, 26*, pp. 39–68. Available at: https://doi.org/10.28945/5078

National Academies of Sciences, Engineering, and Medicine (2025) Artificial intelligence and the future of work. Washington DC: The National Academies Press. Available at: https://doi.org/10.17226/27644

Nikitas, A., Vitel, A.E. and Cotet, C. (2021) 'Autonomous vehicles and employment: An urban futures revolution or catastrophe?', Cities, 114, Article 103203. Available at: *https://doi.org/10.1016/j.cities.2021.103203*

OECD (2023) OECD employment outlook 2023: Artificial intelligence and the labour market. Paris: OECD Publishing. Available at: *https://doi.org/10.1787/08785bba-en*

OECD (2024) OECD employment outlook 2024: The net-zero transition and the labour market. Paris: OECD Publishing. Available at: *https://doi.org/10.1787/ac8b3538-en*

OECD (2025a) Bridging the AI skills gap: Is training keeping up? Paris: OECD Publishing. Available at: *https://doi.org/10.1787/66d0702e-en*

OECD (2025b) Artificial intelligence and the labour market in Japan. Paris: OECD Publishing. Available at: *https://doi.org/10.1787/b825563e-en*

Parmar, B.L., Freeman, R.E., Harrison, J.S., Wicks, A.C., Purnell, L. and de Colle, S. (2010) 'Stakeholder theory: The state of the art', *Academy of Management Annals, 4*(1), pp. 403–445. Available at: https://doi.org/10.5465/19416520.2010.495581

Peres, R.S., Jia, X., Lee, J., Sun, K., Colombo, A.W. and Barata, J. (2020) 'Industrial artificial intelligence in industry 4.0 – systematic review, challenges and outlook', IEEE Access, 8, pp. 220121–220139. Available at: *https://doi.org/10.1109/ACCESS.2020.3042874*

Poghosyan, S., Harutyunyan, A., Poghosyan, M., Nalbandyan, H., Beglaryan, L., Adonts, N., Azatyan, L. and Asatryan, H. (2026) 'Reskilling human capital in the AI era: a human-centric conceptual "spider web" model of knowledge and technology integration', *Cogent Arts & Humanities, 13*(1), Article 2617070. Available at: https://doi.org/10.1080/23311983.2026.2617070

Renieris, E.M., Kiron, D., Mills, S. and Kleppe, A. (2026) *'Beyond the model: why responsible AI must address workforce impact'*, MIT Sloan Management Review.

Rony, M.K.K., Parvin, M.R., Wahiduzzaman, M., Debnath, M., Bala, S.D. and Kayesh, I. (2024) '"I wonder if my years of training and expertise will be devalued by machines": Concerns about the replacement of medical professionals by artificial intelligence', *SAGE Open Nursing, 10*, pp. 1–17. Available at: https://doi.org/10.1177/23779608241245220

Schultz, T.W. (1961) 'Investment in human capital', *American Economic Review, 51*(1), pp. 1–17.

Sharfuddin, R. (2025) A proactive response to AI-driven job displacement. Mercatus Policy Brief. Mercatus Centre at George Mason University. Available at: *https://www.mercatus.org/research/policy-briefs/proactive-response-ai-driven-job-displacement*

Sharma, V., Deb, S., Mahajan, Y., Ghosal, A. and Kapse, M. (2025) 'Psychological impacts of AI-induced job displacement among Indian IT professionals: A Delphi-validated thematic analysis', *International Journal of Qualitative Studies on Health and Well-being, 20*(1), Article 2556445. Available at: https://doi.org/10.1080/17482631.2025.2556445

Snyder, H. (2019) 'Literature review as a research methodology: An overview and guidelines', *Journal of Business Research, 104*, pp. 333–339. Available at: https://doi.org/10.1016/j.jbusres.2019.07.039

UC Berkeley Labor Center (2024) What workers and unions stand to gain from recent executive orders on artificial intelligence. Available at: *https://laborcenter.berkeley.edu/what-workers-and-unions-stand-to-gain-from-recent-executive-orders-on-artificial-intelligence/*

Urban Institute (2025) How government can embrace AI and workers. Available at: *https://www.urban.org/urban-wire/how-government-can-embrace-ai-and-workers*

World Economic Forum (2025) Future of jobs report 2025. Geneva: World Economic Forum. Available at: *https://www.weforum.org/publications/the-future-of-jobs-report-2025/*

World Economic Forum (2026) Four futures for jobs in the new economy: AI and talent in 2030. Geneva: World Economic Forum. Available at: *https://reports.weforum.org/docs/WEF_Four_Futures_for_Jobs_in_the_New_Economy_AI_and_Talent_in_2030_2025.pdf*