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From Technological Substitution to Institutional Response: A Systematic Review of Anxiety, Resistance, and Governance Transformation among Low Skilled Workers in the Age of Artificial Intelligence

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Abstract

Artificial intelligence and robotic technologies are fundamentally reshaping labour markets and pose multifaceted challenges to workers engaged in routine and low-skilled tasks. This study reviews the principal scholarly contributions from both domestic and international literature over the past decade. Extensive empirical evidence shows that AI and robotics can substitute for rule-based, codifiable routine tasks, leading to contractions in low-skilled occupations and downward pressure on wages, with displacement effects extending from manufacturing into cognitive roles such as clerical work and customer service. Yet displacement is not the whole story: when firms adopt AI as an augmentative tool rather than a replacement mechanism, it can raise worker productivity and contribute to job creation. In terms of wages and job quality, automation has intensified income inequality between high-skilled and low-skilled workers, while algorithmic management and monitoring have reduced employees' autonomy and perceived work meaningfulness, contributing to "AI anxiety", characterised by persistent concerns about job loss, skill obsolescence, and diminished control. Survey evidence further suggests that public attitudes towards AI combine optimism with apprehension, and that most respondents oppose granting AI systems final authority over hiring and dismissal decisions. In response, trade unions have increasingly pursued algorithmic transparency and stronger technology governance rights through collective bargaining, and governments are accelerating legislative initiatives to establish and protect workplace technology rights. This review highlights clear gaps in existing research, including limited evidence from developing-country contexts, insufficient attention to within-occupation heterogeneity, an incomplete account of the psychological mechanisms underlying AI anxiety, and a shortage of rigorous evaluations of reskilling policy effectiveness; future research should therefore strengthen cross-national comparisons, longitudinal tracking, and interdisciplinary collaboration to support the development of a technology governance framework that balances efficiency with equity.

Keywords

artificial intelligence; frontline workers; employment displacement; wage polarisation; AI anxiety; collective bargaining

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1 Employment Displacement Effects Induced by AI Technologies

1.1 Automation of Low Skilled Jobs and Cross Sectoral Diffusion

A substantial body of high quality empirical research has accumulated on the displacement effects of artificial intelligence and industrial robots on low skilled occupations, with a central insight pointing to structural transformation at the task level rather than simple shifts across industries. Autor, Levy, and Murnane (2003) argue within the framework of task based technological change that computerisation tends to substitute routine tasks that are rule based, codifiable, and repetitive, while complementing non routine analytical and interactive activities. Building on this theoretical foundation, Acemoglu and Restrepo (2017, 2020) employ an instrumental variable strategy using data from United States commuting zones between 1990 and 2007 to identify the causal impact of robot penetration. Their findings indicate that the addition of one industrial robot reduces employment by approximately 0.18 to 0.34 percentage points per thousand workers and lowers wages by around 0.25 to 0.5 percent, with adverse effects concentrated among low skilled workers and routine manufacturing occupations. Cross national evidence supports similar conclusions. Graetz and Michaels (2018), using data from seventeen advanced economies, show that while robots significantly enhance labour productivity and value added, they also reduce the labour share of income, thereby generating skill biased distributional effects. Evidence from Germany highlights the importance of institutional buffering. Although robots exhibit a clear substitution effect on routine manufacturing roles, the presence of a well developed vocational training system has prevented substantial net employment losses (Dauth et al., 2017). Taken together, these findings suggest that AI and robotic technologies possess strong substitution potential for programmable, standardised, and highly repetitive low skilled tasks, and that their aggregate employment impact depends to a considerable extent on national institutional arrangements and the adaptability of labour market structures. In recent years, with the rapid advancement of algorithmic technologies and generative artificial intelligence, displacement effects have expanded beyond traditional manufacturing into cognitive and clerical domains. Eloundou et al. (2023), based on occupational task databases, estimate that approximately eighty percent of the United States workforce is exposed to the influence of large language models in at least ten percent of their tasks, with the highest exposure observed in low skilled clerical and routine cognitive roles. Brynjolfsson, Li, and Raymond (2023), through firm level field experiments, find that generative AI tools significantly enhance productivity in customer service functions, with particularly pronounced gains

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among lower performing employees, thereby reshaping existing skill premium structures. Firm level studies in China report consistent patterns. Zhou and Jin (2022), using panel data from industrial enterprises between 2010 and 2019, demonstrate that AI investment increases demand for high and medium skilled labour while reducing the share of low skilled employment, reflecting a clear upgrading of labour structures. Data from the International Federation of Robotics (2023) further indicate that China has become the largest adopter of industrial robots globally, with robot density rising rapidly in highly repetitive sectors such as automotive, electronics, and machinery manufacturing, thereby intensifying substitution pressures on low skilled positions.

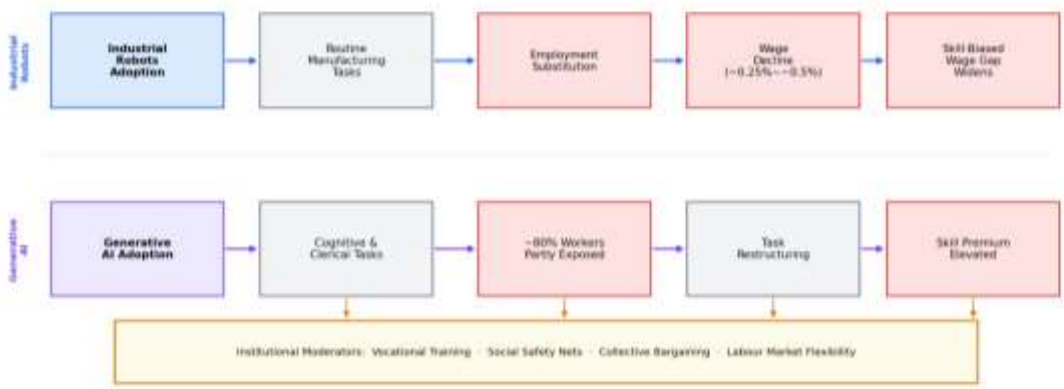

Figure 1 AI / Automation Substitution Mechanism for Low-Skill Workers

1.2 The Dual Logic of Task Selective Disruption and Capability Enhancement

An increasing number of studies have moved beyond broad classifications at the industry or occupational level and now examine the specific tasks embedded within jobs in order to assess the actual degree of exposure to artificial intelligence. This line of inquiry reveals a critical insight: the impact of AI is strongly task selective. Research that applies natural language processing techniques to recruitment texts and job descriptions shows that roles involving a higher share of structured and rule based cognitive tasks exhibit significantly greater exposure to AI and are therefore more susceptible to substitution pressures in labour demand (Henseke et al., 2025). However, greater exposure does not necessarily lead to a unidirectional contraction in total employment. Empirical analysis by Acemoglu et al. (2022) indicates that although tasks with higher exposure are more likely to experience reduced labour demand, efficiency gains released through technological adoption and the resulting demand expansion effects operate simultaneously. As a result, aggregate employment outcomes reflect a far more complex net effect than the simplified narrative that equates

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substitution with job loss. Firm level observations further support this perspective. Oliveira et al. (2025) find that AI investment is often accompanied by a reconfiguration of internal task structures, with a declining share of repetitive information processing activities and a corresponding increase in tasks requiring judgement, communication, and coordination. Collectively, these findings point to a central conclusion that AI does not exert uniform effects across occupations but instead penetrates selectively according to task characteristics. Micro level empirical evidence from firms further illuminates the mechanisms through which capability enhancement operates in practice. Brynjolfsson et al. (2025), in a longitudinal study of generative AI assistants introduced in call centres, document significant improvements in overall productivity following technological integration. Performance gains are particularly pronounced among less experienced workers, resulting in a narrowing of performance disparities across employees without observable increases in layoffs. The study suggests that AI tools primarily function by offering real time guidance and knowledge support, thereby enhancing the efficiency and quality of task completion, positioning them more as capability amplifiers than as direct substitutes for human labour. Similar patterns are observed in other knowledge intensive settings. Experimental research by Noy and Zhang (2023) finds that AI can substantially reduce task completion time and improve output quality, while human involvement remains indispensable in stages involving complex decision making and contextual judgement. Taken together, these findings suggest that when organisations effectively integrate AI into existing workflows through training and process redesign, technological adoption tends to raise workers' marginal productivity and expand overall output rather than simply reduce employment levels. Under appropriate institutional arrangements and organisational adaptation, AI therefore manifests less as a blunt force of labour

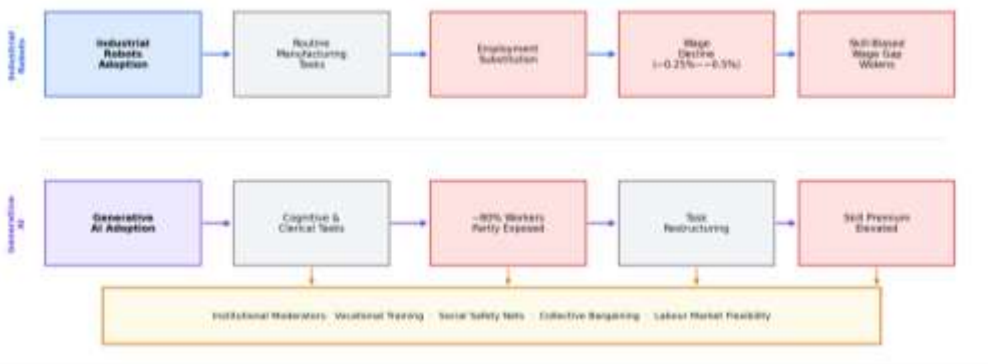

Figure 2 AI / Automation Substitution Mechanism for Low-Skill Workers

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displacement and more as a transformative force reshaping task structures and skill demands.

1.3 Automation Driven Wage Polarisation and Divergence in Skill Returns

Automation has long been regarded as a structural force contributing to wage polarisation. The theory of task oriented technological change provides a clear explanatory framework. When technology substitutes routine cognitive and operational tasks, middle skill occupations are typically affected first, leading to declines in their relative wages and an expansion of income distribution towards both high and low ends (Autor et al., 2003). This theoretical prediction has been widely confirmed in subsequent empirical studies. Acemoglu and Restrepo (2017), using regional data from the United States, show that rising industrial robot density significantly reduces employment rates and wages in affected areas, with the most pronounced negative effects concentrated among middle skill manufacturing workers. Individual level evidence from Germany presents a more nuanced picture. While robot adoption did not result in large scale unemployment, it significantly suppressed long term income growth for certain manufacturing workers while increasing wage returns for high skill technical roles, thereby reinforcing existing skill premium structures (Dauth et al., 2021). Recent studies on artificial intelligence extend this pattern. Firms adopting AI tend to expand high skill positions, particularly in data analysis and technical management, with wage growth in these roles outpacing that of low skill positions, reflecting a clear skill biased effect (Acemoglu et al., 2022). Across countries and time periods, these empirical findings converge on a consistent logic: automation reshapes task structures and production functions in ways that raise the marginal productivity of high skill labour while exerting sustained downward pressure on the incomes of middle and low skill workers, thereby intensifying wage inequality. Importantly, the widening of wage disparities driven by automation does not stem solely from the direct substitution of jobs by technology. Changes in corporate human resource strategies and patterns of skill investment also play a critical role. OECD based research drawing on multinational employer surveys indicates that most managers expect the impact of AI to fall disproportionately on low skilled and older workers, as these groups face greater challenges in adapting to technological change through retraining (Lane, 2024). Firm level analysis by Babina et al. (2024) provides micro level support for this view. AI investment is significantly associated with increased recruitment of external high skill talent, but shows no comparably strong relationship with training investments for internal low skill employees, suggesting that firms tend to pursue technological upgrading through skill substitution rather than skill enhancement. Cross industry research on digital transformation further deepens

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this understanding. Technology adoption significantly increases wage premiums for highly educated workers and widens internal pay dispersion within firms, particularly in knowledge intensive sectors (Bessen et al., 2023). Taken together, these findings indicate that automation drives wage polarisation through multiple channels and at multiple levels. Beyond compressing income opportunities for middle and low skill workers through direct substitution, it reshapes hiring preferences and skill investment strategies in ways that reinforce disparities in skill returns, thereby entrenching inequality within institutional and organisational structures of income distribution.

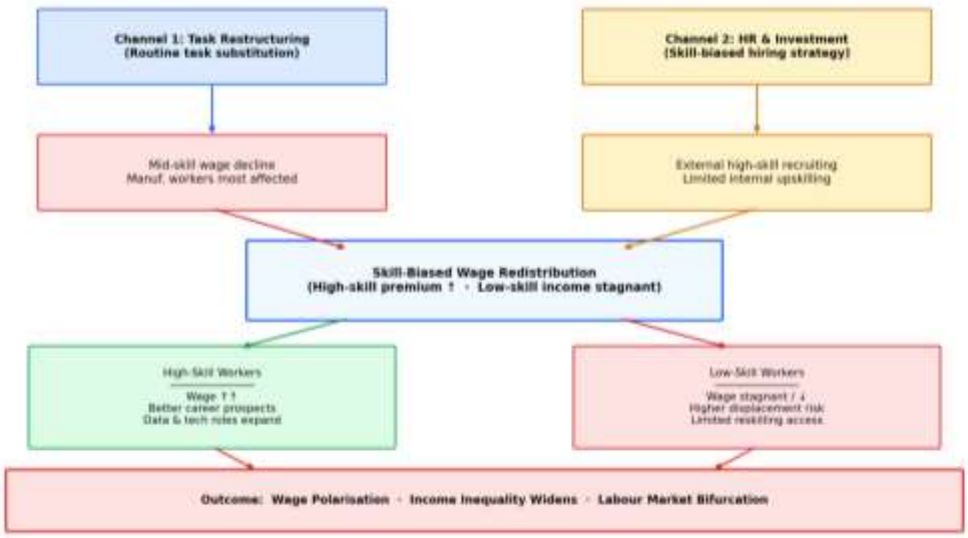

Figure 3 Automation and Wage Polarisation: Dual-Channel Mechanism

2 AI, Wages, Job Quality, and Working Conditions

2.1 Skill Biased Wage Redistribution and Income Compression among Frontline Workers

The expansion of robotics and artificial intelligence has not affected workers' income levels uniformly but has instead generated pronounced differentiation along skill lines. Acemoglu and Restrepo (2020), drawing on regional data from the United States, were among the first to document this pattern, showing that increases in industrial robot density significantly reduce both employment and wage levels in affected areas, with middle skill manufacturing workers experiencing the most persistent income pressure. Evidence from multiple European countries reveals a similar trend. Rising robot penetration is significantly associated with slower wage growth among low skill workers, while wage returns for high skill positions remain stable or even increase, producing a skill biased redistribution of income (Graetz and Michaels, 2018). In the Chinese context, Zhou and Jin (2022), using firm level data, find that

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investment in artificial intelligence significantly reduces the employment share of low skill workers while increasing the wage share of high skill workers, indicating that technological progress is fundamentally reshaping income distribution structures. Research by Bessen et al. (2023) on automation and internal wage structures within firms further confirms this trajectory. In enterprises that rapidly adopt automation technologies, wage dispersion widens, skill premiums increase, and real wage growth for low skill positions lags behind. Taken together, cross national and cross sectoral evidence suggests that the wage effects of automation are not characterised by an overall decline in average earnings but rather by a systematic widening of income disparities across skill groups through changes in job structures and skill demand. Beyond reshaping wage distributions, artificial intelligence also profoundly influences workers' career trajectories and income stability. Acemoglu et al. (2022), analysing online vacancy data, show that the diffusion of AI related technologies significantly raises hiring salaries for high skill roles such as data analytics, algorithm development, and digital management, while simultaneously reducing demand for routine positions. As a result, skill based wage gaps begin to widen at the point of labour market entry. Longitudinal firm level research by Babina et al. (2024) reveals a parallel dynamic within organisations. Firms with higher levels of automation are more inclined to constrain wage growth in low value added roles and to allocate resources towards high skill employees through performance based incentives, leading to increasing internal wage differentiation. These two strands of evidence converge on a concerning reality. As labour markets shift towards high skill roles, frontline workers who fail to upgrade their skills face not only prolonged wage stagnation but also greater exposure to employment instability. Overall, existing empirical research consistently indicates that robotics and artificial intelligence restructure wage systems through skill biased mechanisms. Their primary impact lies not in changes to average wage levels but in the deeper reconfiguration of income distribution, with frontline workers occupying the most vulnerable position within this transformation.

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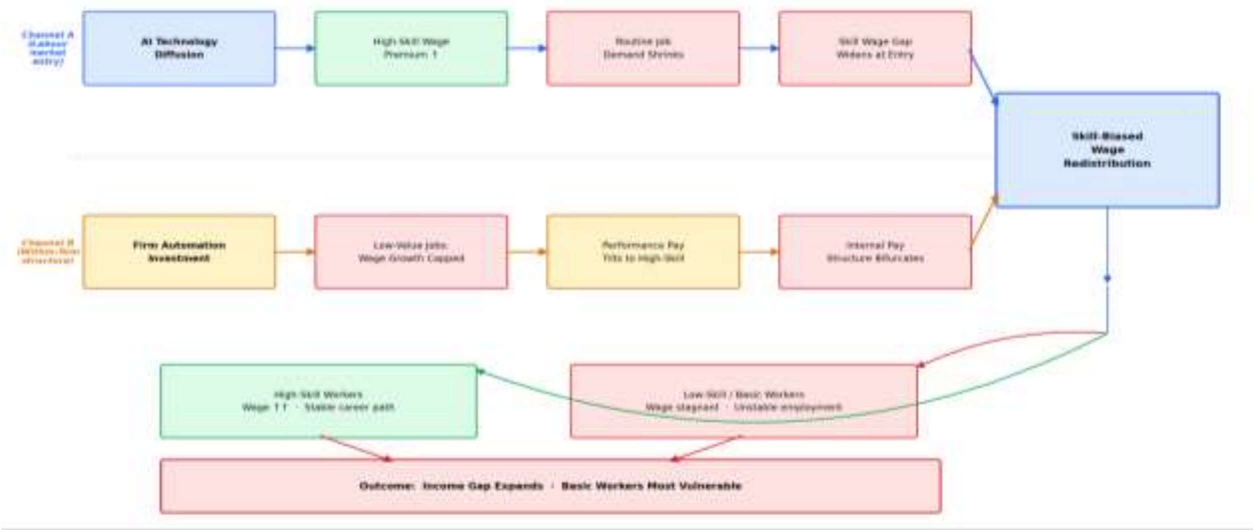

Figure 4 Skill-Biased Wage Redistribution: How AI Reshapes Income Distribution

2.2 The Conditional Erosion of Work Autonomy and Meaning under Automation

The impact of artificial intelligence and robotic technologies on the world of work extends beyond employment levels to encompass job quality and workers' subjective experiences. Using micro survey data from multiple European countries, Nikolova et al. (2024) identify a concerning relationship between rising robot density and declining perceptions of work meaningfulness and autonomy among employees. This negative association is particularly pronounced among low skill workers engaged in repetitive tasks, while those performing computer based or monitoring roles appear to be less affected. Longitudinal evidence from the United Kingdom supports this pattern from another perspective, showing that jobs characterised by higher degrees of technological automation tend to involve greater task standardisation and more intensive performance monitoring, thereby gradually reducing employees' decision making space and sense of control over their work (Felstead and Reuschke, 2021). When the analytical lens shifts from industrial automation to algorithmic management, the implications become even more evident. Empirical analysis by Wood et al. (2021) demonstrates that when task allocation and supervision are fully delegated to algorithmic systems, workers are more likely to experience diminished autonomy and increased feelings of work alienation, a pattern particularly prevalent in platform based and highly proceduralised industries. Taken together, these cross national and cross sectoral findings suggest a consistent trajectory in which automation reshapes task structures and management practices in ways that erode workers' perceived control and sense of meaning, with low skill groups bearing the greatest burden. Yet this negative outlook does not capture

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the full complexity of technological change, and a growing body of research highlights the heterogeneous effects of AI on work experience. Genz et al. (2023), drawing on employee survey data from German firms, find that in organisations where digital technologies are used to support rather than replace human decision making, workers report higher levels of job satisfaction and more effective use of their skills. This finding underscores that outcomes are not determined by technology itself but by how it is embedded within organisational structures. Experimental research on human machine collaboration by Parker and Grote (2022) further supports this view. When AI is designed as an assistive tool rather than a coercive control mechanism, employees are more likely to perceive enhanced competence and greater task accomplishment rather than a loss of control. Cross national comparative research by Eurofound (2023) extends the analysis to the institutional level, showing that supportive institutional environments and firm level training investments can mitigate the negative effects of automation on work autonomy. In organisations that prioritise employee participation and skill development, the adverse impact of technological adoption on subjective wellbeing is significantly reduced. When these contrasting strands of evidence are considered together, a more cautious conclusion emerges. The influence of AI on work autonomy and meaning is not unidirectional but depends critically on the interaction between task characteristics, management models, and institutional arrangements. Where technology is primarily deployed to intensify monitoring and standardisation, low skill workers are most likely to experience diminished autonomy, whereas in organisational contexts that emphasise collaboration and capability enhancement, the same technologies may foster more positive work experiences.

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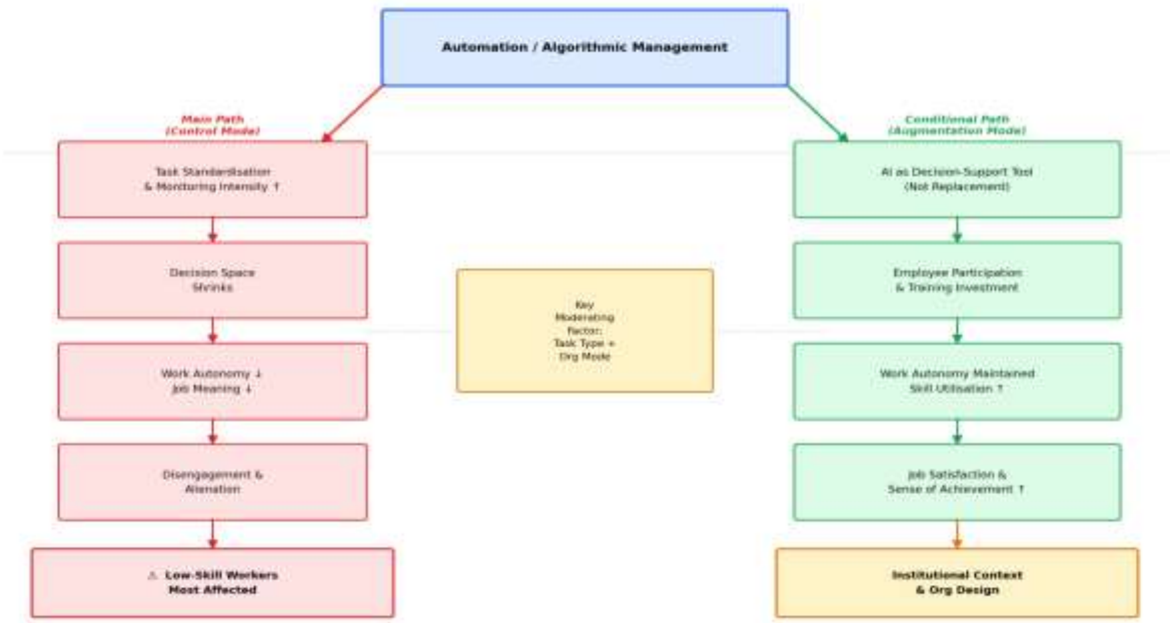
Figure 5 Automation's Conditional Effects on Work Autonomy and Meaning



2.3 The Psychological Mechanisms and Group Differentiation of AI Anxiety

The rapid diffusion of artificial intelligence has given rise to a multidimensional psychological phenomenon among workers commonly referred to as AI anxiety. Drawing on integrated fear acquisition theory, Li and Huang (2020) conceptualise AI anxiety as a composite construct encompassing concerns such as fear of unemployment, learning related stress, and perceived socio technological marginalisation, thereby providing a conceptual anchor for subsequent empirical inquiry. Reports on workplace psychology and wellbeing further extend this definition to include worries about skill obsolescence, loss of autonomy, and continuous algorithmic evaluation (Meditopia, 2026). Survey data from the Pew Research Center offer large scale empirical support for these concerns, showing that a significantly higher proportion of United States workers feel more apprehensive than optimistic about the future impact of AI on work (Lin and Parker, 2025). Such sentiments tend to be particularly pronounced among low income and low skill groups, who face greater risks of job displacement and possess fewer resources for occupational transition (Lane, 2024). At the micro level, AI anxiety is not merely a subjective perception but is consistently associated with measurable workplace outcomes. Yam et al. (2023), through six studies incorporating archival analysis, preregistered experiments, and experience sampling, find that both physical and psychological exposure to robotics significantly increase employees' sense of job insecurity, which in turn predicts higher levels of burnout and workplace deviance across

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diverse cultural and industrial contexts. Similarly, Kong et al. (2021), using data from hotel industry employees, report that heightened awareness of AI is significantly linked to reduced occupational efficacy and increased burnout, suggesting that perceptions of technological change alone may function as antecedents of psychological strain. While these studies establish a clear link between AI anxiety and adverse workplace outcomes, recent research has begun to unpack the underlying mechanisms that transmit anxiety into deeper emotional consequences. Cheng et al. (2025), using a three wave panel survey of employees in Chinese private enterprises, find that AI adoption does not directly induce burnout but exerts an indirect effect through elevated job stress, while learning self efficacy related to AI significantly buffers this relationship. Li et al. (2025) identify an alternative transmission pathway in which AI awareness operates through a chain mediation involving job insecurity and work to family conflict, ultimately leading to emotional exhaustion. This finding indicates that anxiety triggered by AI extends beyond the workplace and spills over into family life. Xu et al. (2025), examining service sector workers, show that AI related workplace anxiety influences life satisfaction primarily through negative emotional responses, with social support serving as an effective moderating factor that mitigates this adverse pathway. Notably, these psychological effects exhibit clear group heterogeneity. Workers in low skill roles, which typically require limited specialised knowledge or complex cognitive ability, are more susceptible to fears of technological replacement (Xu et al., 2025), while organisational practices such as corporate social responsibility can buffer the relationship between AI adoption and employee depression (Manzoor et al., 2025). Taken together, AI anxiety emerges as a complex psychological process shaped by technological exposure, individual psychological resources, organisational support, and institutional arrangements. Its implications for the wellbeing of frontline workers extend far beyond the commonly assumed concern of job loss and warrant sustained scholarly attention.

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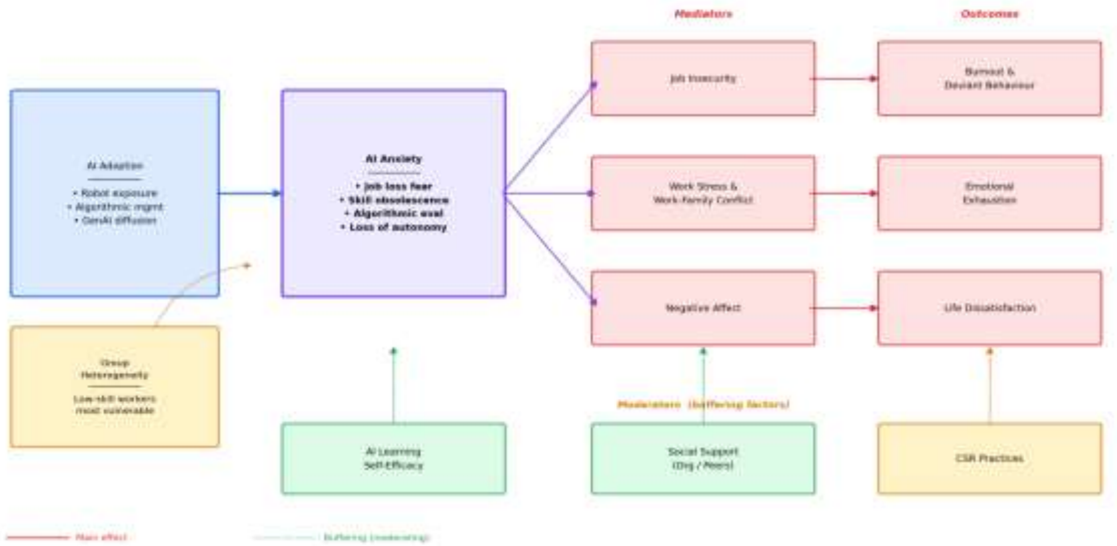

Figure 6 AI Anxiety: Psychological Mechanism and Group Differentiation

3 Worker Attitudes and Resistance in the Age of AI

3.1 The Fragmented Structure of Worker Perceptions of AI and Stratified Patterns of Adoption

A growing body of large scale survey evidence reveals a recurring feature in workers' perceptions of artificial intelligence: a complex structure in which concern coexists with expectation, and awareness does not necessarily translate into trust. Surveys conducted by the Pew Research Center show that workers in the United States are generally more worried than optimistic about the impact of AI on work, while the proportion of individuals actually using AI in their jobs remains relatively low, with clear generational and educational differences in adoption (Lin and Parker, 2025). Longitudinal data place this concern within a broader temporal context. Among the United States public, 51 percent report feeling more worried than excited about the increasing use of AI in daily life, a figure that has steadily risen since 2021, whereas only 15 percent of AI experts express similar concerns, highlighting a pronounced perception gap between the general public and professional communities (Pew Research Center, 2025). This sense of unease is not confined to the United States. Ipsos, drawing on annual surveys across 32 countries, finds that approximately half of respondents globally feel nervous about AI based products and services, with this proportion rising by 13 percentage points since 2022. Skepticism is most pronounced in Anglophone and European contexts, while attitudes in many Asian countries remain comparatively more optimistic (Ipsos, 2024). Global workplace data from the ADP Research Institute reveal a more nuanced internal divergence. While most employees believe AI will influence their work in the near

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future, opinions differ sharply regarding its direction, with some anticipating support and enhancement and others fearing partial displacement (ADP Research Institute, 2024). Mixed methods research by Brougham and Haar (2018) captures this cognitive tension at the individual level. Although many employees are aware through media exposure of the potential employment impact of automation, only a minority believe their own roles are directly at risk. Nonetheless, increased awareness of smart technology, artificial intelligence, robotics, and algorithms is significantly associated with lower organisational commitment, stronger turnover intentions, and greater cynicism, indicating that perceptions of technological change alone can shape occupational attitudes even in the absence of actual displacement. At the behavioural level, public patterns of AI adoption display marked stratification, accompanied by an intriguing mismatch between frequency of use and trust. A global survey jointly conducted by the University of Melbourne and KPMG, covering more than 48,000 respondents across 47 countries, finds that although 66 percent report frequent use of AI, only 46 percent express trust in such systems. A substantial share of users rely on AI outputs without verifying their accuracy, and 56 percent report having made workplace errors linked to AI use (Gillespie et al., 2025). This paradox of reliance without trust is unevenly distributed across demographic groups. Younger individuals, those with higher incomes, and those with higher educational attainment are more likely to engage actively with AI and hold favourable attitudes, whereas older individuals, less educated groups, and workers in service sectors exhibit higher levels of non use and resistance (Ipsos, 2024; Lin and Parker, 2025). Cross national comparative research further demonstrates how institutional and cultural contexts shape technological perceptions. Brougham and Haar (2020), in a study spanning Australia, New Zealand, and the United States, find that perceptions of technological disruption significantly predict job insecurity, which in turn mediates the relationship between perceived technological change and turnover intentions. Notably, respondents in the United States report significantly higher levels of perceived technological threat than those in Australia and New Zealand. Taken together, these findings indicate that workers' perceptions of AI are neither purely supportive nor purely oppositional but instead constitute a composite structure in which optimism and anxiety coexist, shaped by the interplay of skill levels, occupational roles, and national institutional and cultural environments (ADP Research Institute, 2024; Lane, 2024).

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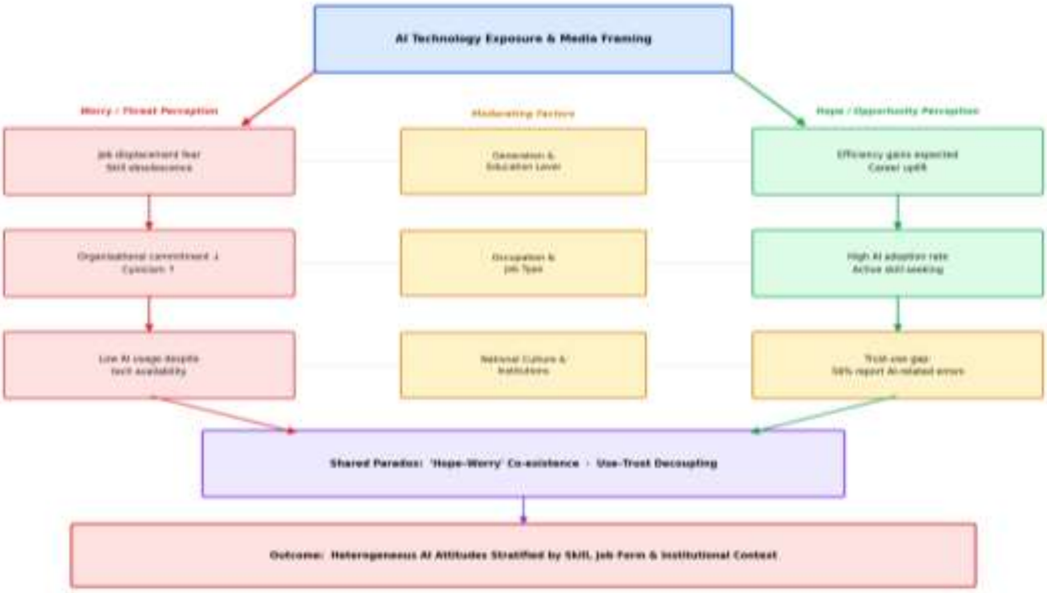

Figure 7 Split Cognitive Structure of Worker AI Perception and Layered Adoption Behaviour

3.2 The Rise of Collective Bargaining as a Tool of Technological Governance and Institutional Divergence

In response to the pressures of job displacement and algorithmic monitoring brought about by artificial intelligence, trade unions and collective bargaining have increasingly expanded beyond traditional concerns such as wages and working hours into the domain of technological governance, gradually becoming a central institutional mechanism through which workers seek a voice in the automation process. Research by the International Labour Organization provides a normative framework for this trend, emphasising the role of social dialogue in shaping the adoption of AI, with the aim of ensuring that technology complements rather than replaces labour, empowers rather than controls employees, and integrates technological disruption into systems of social protection (International Labour Organization, 2025). Recent developments suggest that these principles are being translated into concrete contractual provisions. In the United States film and television industry, the Writers Guild reached an agreement with major studios after a 148 day strike, stipulating that AI must not be used to undermine writers' authorship rights and requiring disclosure of any AI generated material provided to writers. This agreement is widely regarded as the first industry level collective accord regulating the use of AI (Kinder, 2024). Kelley (2024) systematically documents how strikes by both the Writers Guild and SAG AFTRA have shifted AI governance from policy debate into contractual practice. Increasingly, unions are establishing AI committees, issuing policy statements, and incorporating technological issues into regular

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bargaining agendas, signalling an emerging institutionalisation of collective action. Similar dynamics are evident in the logistics sector. The International Longshoremen's Association launched a strike in October 2024 demanding a complete ban on fully automated port equipment, and a collective agreement reached in early 2025 included provisions prohibiting the introduction of fully unmanned technologies unless approved by unions or subject to arbitration (Baker McKenzie, 2025). In the transportation sector, the Teamsters' agreement with UPS following a nationwide strike in 2023 targeted algorithmic surveillance by restricting the use of in vehicle monitoring cameras and establishing a joint labour management technology review committee to ensure advance notice of any technological changes affecting working conditions or employment levels (Glass, 2024). While these examples are largely drawn from the United States, cross national comparative research illustrates how institutional contexts shape the pathways and effectiveness of collective action. Doellgast, Wagner, and O Brady (2023), through matched case studies of call centres in Germany and Norway, find that worker representatives in both countries are able to impose meaningful constraints on algorithmic management, though they rely on different sources of institutional power. In Germany, works councils leverage strong co determination rights to secure comprehensive agreements that prohibit the use of individual performance data for disciplinary action and restrict video surveillance. In Norway, unions achieve similar outcomes through the enforcement of data protection legislation and informal social dialogue mechanisms. Building on these findings, Doellgast et al. (2025), in a working paper prepared for the International Labour Organization, identify three key conditions for effective social dialogue across countries: institutional constraints on employer outsourcing and exit strategies, legal support for collective worker voice, and inclusive solidarity strategies. Evidence from Eurofound similarly indicates that references to AI in collective bargaining agreements have increased significantly since 2024. In Denmark, the Hilfr2 platform agreement incorporates algorithmic task allocation and performance evaluation into collective bargaining frameworks, while sectoral agreements in Spain's banking and insurance industries introduce provisions addressing algorithmic transparency, limitations on misuse, and access to retraining (Eurofound, 2025). Nevertheless, these institutional practices remain concentrated in economies and sectors with strong union presence. In regions and industries lacking collective organisation, worker rights are more likely to be overlooked. As observed by Doellgast, employees in non unionised workplaces in the United States often lack both information and participation rights regarding employer use of AI and are left to experience only its consequences. Consequently, integrating collective bargaining with legislative

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protections to establish broader technological governance mechanisms remains a pressing challenge for both policy and scholarly inquiry (International Labour Organization, 2025).

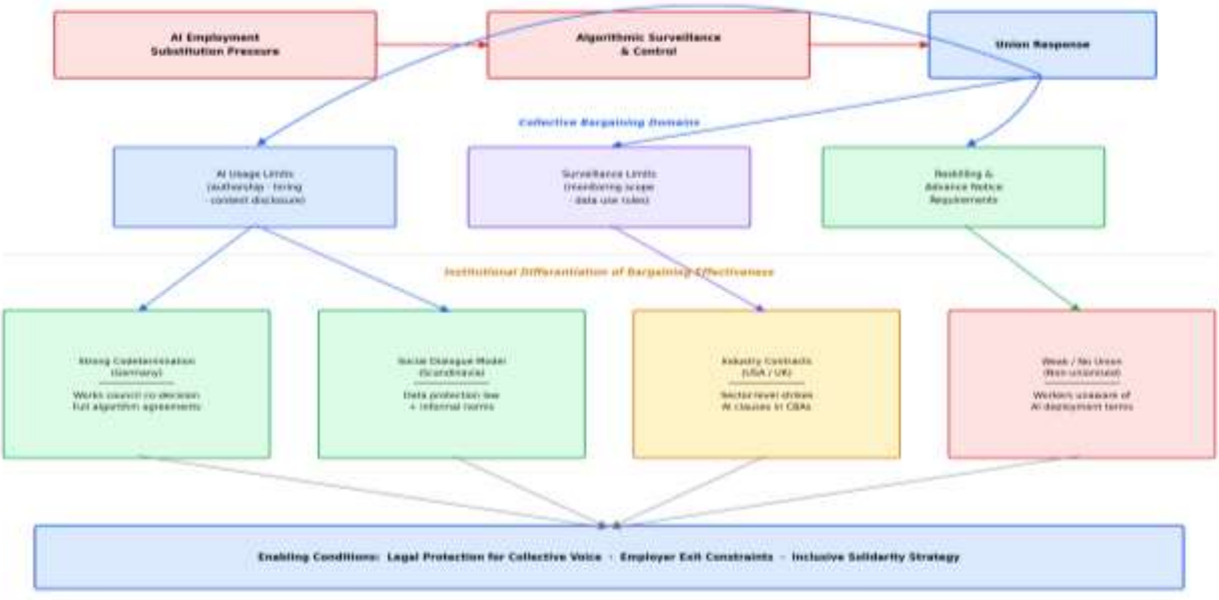

Figure 8 Collective Bargaining as Technology Governance: Rise and Institutional Differentiation

3.3 Worker Resistance under Algorithmic Surveillance and the Institutionalisation of Workplace Technology Rights

The rapid expansion of algorithmic surveillance in the workplace is triggering widespread resistance that extends from shop floors to legislative arenas. Investigative reporting by Greenhouse (2024) highlights the everyday realities of this transformation, showing that in sectors such as warehousing, call centres, and retail, the deep integration of AI monitoring tools with performance based disciplinary systems subjects workers to sustained pressure and intensifies concerns over privacy violations and forms of digital authoritarianism. Academic research provides a more systematic analytical framework for these frontline observations. Bernhardt, Kresge, and Suleiman (2023) demonstrate that employer use of data driven management practices, including employee data collection, electronic monitoring, and algorithmic decision making, now permeates core human resource functions such as recruitment, performance evaluation, scheduling, and termination. The resulting risks include discriminatory bias, skill erosion, unsafe work pacing, and the erosion of autonomy and dignity, while existing regulatory frameworks remain largely silent on workplace technology rights. Kellogg, Valentine, and Christin (2020), in their influential review, conceptualise algorithmic management as a new contested terrain of organisational control. They identify

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four primary functions through which algorithms exert authority over workers, namely direction, evaluation, discipline, and replacement, and note that the opacity of algorithmic systems presents unprecedented challenges to traditional forms of worker protest and negotiation. In response, worker resistance has taken diverse forms. Cross (2024), drawing on in depth interviews with union leaders in the United States, finds that unions are increasingly attentive to electronic surveillance and have achieved some success through collective bargaining and policy advocacy. However, limited union density and high workload pressures constrain their reach, leaving workers in non unionised sectors without effective protection. In platform based economies where formal institutional safeguards are even weaker, resistance often assumes more grassroots forms. In Southeast Asia, delivery drivers and ride hailing workers have formed thousands of mutual aid groups and online communities in the absence of formal union support, mobilising collective petitions, information sharing, and strikes to challenge algorithmic dispatch systems and rating mechanisms (Cheong, 2024). Public opinion research reinforces the breadth of this resistance. Surveys by the Pew Research Center indicate that a majority of Americans oppose the use of AI to track employee movements or monitor working time and reject granting AI systems final authority over employment decisions (Pew Research Center, 2023). Worker dissatisfaction and resistance are increasingly translating into institutional reform, with legislative initiatives addressing data rights and algorithmic accountability gaining momentum across jurisdictions. In the United States, several legislative proposals directly confront workplace surveillance. The proposed Stop Spying Bosses Act would require employers to disclose monitoring and data collection practices and explicitly prohibit surveillance of employees engaged in union activities (Kelley, 2024). State level initiatives such as California's Workplace Technology Accountability Act and New York's Bossware and Oppressive Technology Act mandate impact assessments prior to the deployment of algorithmic management systems, restrict excessive monitoring, and establish grievance mechanisms (NELP, 2025). In 2024, former General Counsel of the National Labor Relations Board Jennifer Abruzzo warned that pervasive monitoring and algorithmic management tools may infringe upon workers' rights to organise under the National Labor Relations Act (NELP, 2025). Legislative developments are equally active in Europe. The UK Trades Union Congress proposed an AI and Employment Rights Bill requiring employers to consult workers before deploying high risk AI systems, ensure transparency, and provide personalised explanations for AI driven decisions, while classifying dismissals based on unjust reliance on AI as automatically unfair (Baker McKenzie, 2025). At the supranational level, the European Union's Artificial Intelligence Act establishes more

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fundamental safeguards by prohibiting the use of AI to measure or simulate human emotions in the workplace and imposing mandatory compliance obligations on high risk systems (Doellgast and Schoenbachler, 2025). These legislative efforts across different jurisdictions reflect a shared underlying logic. As data driven management becomes deeply embedded across workplace practices, the protection of workers' technological rights cannot rely solely on individual complaints or corporate self regulation but requires formal institutional rules to restore informational and power symmetry between employers and employees (Bernhardt et al., 2023).

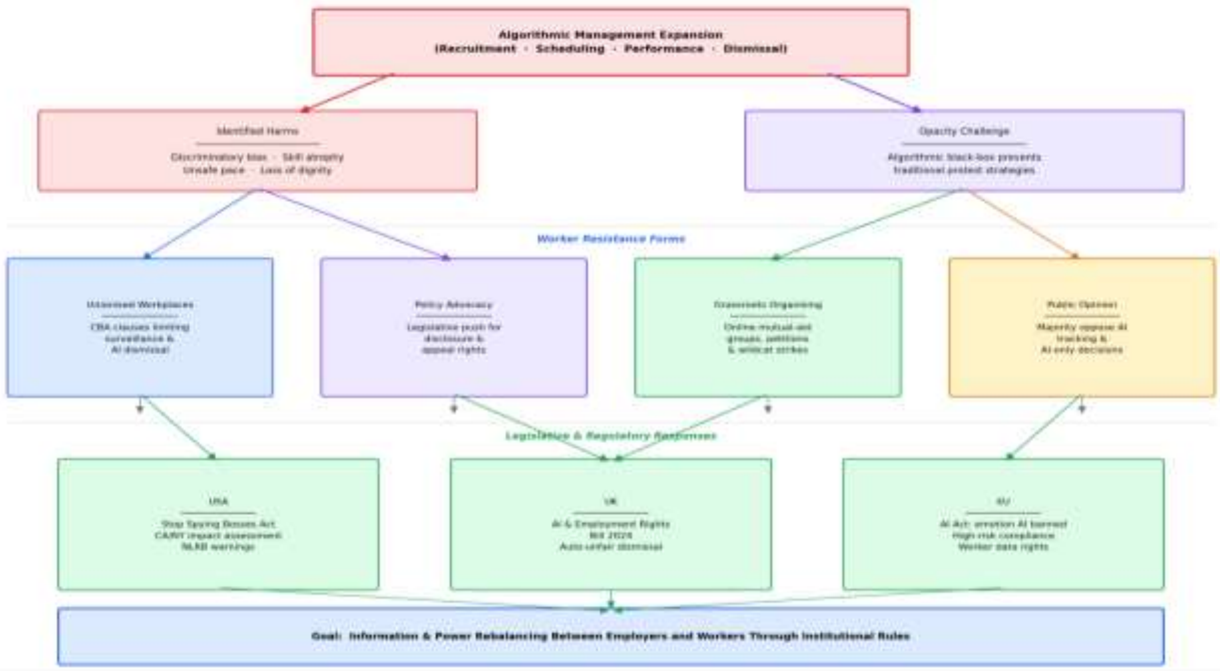

Figure 9 Algorithmic Surveillance Resistance and Workplace Technology Rights

4 Research Gaps and Future Directions

Although existing literature has generated substantial empirical evidence on the effects of artificial intelligence on frontline workers across multiple dimensions, including employment displacement, wage divergence, deterioration of job quality, and psychological impacts, a comprehensive assessment reveals several persistent knowledge gaps. First, high quality causal identification studies remain heavily concentrated in high income economies such as the United States and Germany. The mechanisms and consequences of technological disruption facing low and middle skill workers in developing countries may differ significantly, particularly in contexts characterised by large informal sectors and weak social protection systems, where empirical evidence remains scarce (International Labour Organization, 2025). Second, most studies treat low skill workers as a homogeneous group, overlooking variation across specific occupations such as logistics, caregiving, food services, and cleaning, and rarely incorporating structural vulnerabilities related to gender, ethnicity, or migration status (Lane, 2024). Third, while AI anxiety has been consistently linked to burnout, emotional exhaustion, and turnover intentions (Yam et al., 2023; Li et al., 2025), its deeper psychological transmission mechanisms remain insufficiently theorised and longitudinally validated. The interactive roles of perceived loss of control, fairness perceptions, and organisational trust in shaping resistance behaviours have yet to be integrated into a coherent causal framework. Fourth, evaluations of retraining and skill upgrading policies largely rely on cross sectional analysis and lack longitudinal studies employing strong identification strategies to determine under what conditions such interventions are genuinely effective (Lane, 2024). Fifth, although collective bargaining has emerged as a governance tool in several North American and European cases, there is limited cross national comparative research on how workers in low union density contexts mobilise resistance and claim technological rights in the absence of formal institutional support. In light of these gaps, future research can proceed along several directions. At the geographical level, empirical frameworks should be extended to developing countries and emerging economies, with particular attention to the interaction between informal employment structures, fragile welfare systems, and technological disruption, thereby avoiding the uncritical generalisation of high income country experiences. At the level of analytical granularity, research should move beyond the broad category of low skill work to examine intra occupational and task level dynamics, incorporating intersectional variables such as gender, race, and migration status to uncover differentiated pathways of technological impact. At the psychological level, future studies should develop integrative theoretical models that situate AI anxiety, perceived control, organisational trust, and fairness perceptions within a unified framework, supported by longitudinal designs and preregistered experiments to establish causal mechanisms rather than relying solely on cross sectional correlations. In terms of policy evaluation, quasi experimental methods and randomised controlled trials are needed to rigorously assess the effectiveness of interventions such as retraining programmes, income support, and algorithmic audits, particularly with respect to their long term implications for employment stability and psychological wellbeing among frontline workers. Finally, at the institutional level, systematic comparisons across governance models should be strengthened, examining the relative effectiveness of collective bargaining, legislative

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regulation, and corporate self governance in constraining algorithmic management and safeguarding technological rights. In low union density and platform dominated environments, understanding how grassroots resistance interacts with formal institutional development represents a critical challenge for both theory and policy (International Labour Organization, 2025; Doellgast et al., 2025).

5 In Depth Discussion of the Impact of Artificial Intelligence on Frontline Workers

The substitutive and complementary effects of artificial intelligence vary significantly across industries. In manufacturing, highly standardised processes such as assembly, welding, and material handling exhibit the highest levels of automation and are most susceptible to direct replacement by industrial robots. By contrast, in sectors such as healthcare, domestic services, and education, where emotional interaction and manual dexterity remain central, AI more often functions as an assistive tool rather than a direct substitute. Importantly, the introduction of robotics does not simply eliminate jobs. It also generates new roles in maintenance, programming, and system monitoring, thereby creating alternative channels of labour absorption (International Federation of Robotics, 2023). With the rise of generative AI, large language models have demonstrated strong capabilities in handling tasks within cognitive domains such as customer service, legal documentation, and medical consultation. These technologies are increasingly influencing components of many occupations, particularly those related to information processing and text generation (Felten et al., 2023). In practice, chatbots now perform initial consultation tasks, while human workers focus on complex or sensitive issues, though model bias and inaccuracies still require human review and feedback (Brynjolfsson et al., 2023; Hampole et al., 2025). This suggests that technological disruption does not manifest as a uniform replacement of human labour but rather as a differentiated restructuring shaped by task characteristics and industry contexts. Firms adopting generative AI must therefore provide training and establish feedback mechanisms to enable effective human machine collaboration rather than unilateral substitution. From a broader socio economic perspective, the diffusion of AI has widened income disparities while also intensifying spatial inequalities. High skilled workers benefit from technological expertise through higher wages and improved career mobility, whereas low skilled workers whose roles are displaced and who lack opportunities for rapid reskilling may be pushed into lower paid and more precarious employment or even unemployment (Autor et al., 2003; Lane, 2024). These structural changes often display spatial concentration, with affluent urban

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centres attracting talent and capital, while employment opportunities in less developed regions decline further (Lane, 2024). In terms of job quality, robotics and algorithmic management reduce workers' agency within production processes, positioning them increasingly as passive executors of predetermined tasks. Feelings of powerlessness and alienation are particularly acute among low skilled workers engaged in repetitive roles (Nikolova et al., 2024). Migrant and minority workers face additional vulnerabilities due to language barriers, unstable legal status, and structural discrimination, and algorithmic scheduling and performance monitoring may impose disproportionately harsh constraints on these groups (Greenhouse, 2024). For frontline workers, job loss represents not only an economic setback but also a disruption to identity, social networks, and psychological support systems, with potential ripple effects on family stability and community cohesion (International Labour Organization, 2025). Algorithmic management has also fuelled AI anxiety and grassroots resistance, generating new tensions within contemporary labour relations. In platform based sectors such as food delivery and parcel logistics, algorithms allocate tasks, evaluate performance, and determine rewards and penalties, while warehouse systems track worker movements and productivity through scanners and strict targets. These practices have triggered widespread dissatisfaction related to stress and perceived unfairness (Greenhouse, 2024). Public opinion data indicate broad opposition to the use of AI for tracking employee behaviour or monitoring working hours (Pew Research Center, 2023). Loss of control is widely viewed as a central driver of AI anxiety. When workers perceive their livelihoods to be determined by opaque algorithmic systems without meaningful avenues for influence, they are more likely to experience stress, depression, and burnout (Meditopia, 2026). Attitudinal differences across groups further reinforce this pattern, with lower and middle income workers more likely to anticipate reduced employment opportunities and remote workers expressing heightened concern about AI related job impacts (Lin and Parker, 2025; ADP Research Institute, 2024). In response, unions and collective action have played a crucial role in advancing technological governance, negotiating measures such as algorithmic transparency, limitations on the use of AI in layoffs and performance assessments, and prior consultation before automation is introduced (International Labour Organization, 2025; Kinder, 2024). However, in sectors and regions lacking collective representation, worker protections remain fragile, underscoring the importance of cross national comparison and institutional learning. From a policy and governance perspective, addressing the challenges posed by AI to frontline workers requires coordinated progress across education, social protection, and technological regulation. Retraining and skill development programmes are

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widely regarded as essential buffers against technological disruption, yet their effectiveness varies considerably depending on programme quality, financial support for participants, and alignment with local labour market demand (Lane, 2024). Strengthening social safety nets, including unemployment insurance, income support, and portable benefits, is equally critical to ensuring stability during transitional periods (International Labour Organization, 2025). At the regulatory level, the European Union is advancing more stringent governance frameworks for AI, emphasising risk assessment, human oversight, and accountability mechanisms, while debates continue over policy innovations such as robot taxation and universal basic income (Lane, 2024). Ethical considerations surrounding algorithmic decision making also remain salient. Historical biases embedded in training data may produce discriminatory outcomes in recruitment, promotion, and compensation decisions (Bracha and Tang, 2025), while firms' claims of commercial confidentiality in refusing to disclose algorithmic logic further reinforce asymmetries of power (Pew Research Center, 2023). In the long term, the sustainable development of AI will depend on tripartite collaboration among governments, employers, and workers, ensuring that employees are included in decisions surrounding technological adoption and implementation. Such an approach can help ensure that technological progress enhances rather than undermines worker value while balancing industrial transformation, regional equity, and sustainable development (International Labour Organization, 2025).

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