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# Equity in Workforce Adaptation: Who is Left Behind in the AI-Driven Economy?

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**Abstract:** One of the fastest-growing trends in the United States is the integration of artificial intelligence (AI) in the workplace, which has led to new ways of working, innovation, and the increasing inequity between workers. The results indicate that low-skilled employees, older workers, and minorities, including African Americans and Hispanics, are disproportionally affected by these barriers, including automation-related job losses, lack of digital infrastructure, and discrimination by AI-based hiring systems. High-skilled employees, on the other hand, enjoy the increase in productivity, worsening wages, and opportunity gaps. The digital disparity, especially among low-income and rural areas, further limits access to training and technology, which continues to exclude. The review identifies the need to provide inclusive policies, equitable reskilling, and ethical AI systems to address such problems. Based on the evaluation of occupational vulnerabilities, inequality in wages, and systemic obstacles, this paper defines risk groups and offers ways of equal adaptation. The insights are meant to assist policymakers, organizations, and institutions in the education sector in creating a new inclusive economy that will enable all workers to be able to cope with the AI advancements, so that no one is left behind in the emerging labor market.

**Keywords:** Artificial intelligence, workforce equity, job displacement, reskilling, digital divide.

## INTRODUCTION

The integration of artificial intelligence (AI) into the U.S. workforce has fundamentally transformed labor markets, driving unprecedented innovation but raising critical equity concerns. AI technologies, including machine learning, robotic process automation, and predictive analytics, have reshaped industries such as manufacturing, healthcare, and logistics, enhancing productivity but disrupting traditional roles (Autor *et al*., 2020; Frey & Osborne, 2017). Low-skilled workers, older employees, and underrepresented groups, such as African Americans and Hispanics, face disproportionate job losses, with a 12% decline in repetitive roles like assembly line work and retail cashier positions since 2015 (Bessen *et al*., 2019; Acemoglu & Restrepo, 2020). High-skilled workers, however, benefit from AI's complementary effects, experiencing wage growth and increased demand in fields like software engineering (Felten *et al*., 2019; Brynjolfsson & McAfee, 2017). The digital divide exacerbates these disparities, as rural and low-income communities lack access to broadband and training resources (World Bank, 2024; Manyika *et al*., 2019).

This systematic literature review examines peer-reviewed journals from 2015 to 2025 to address the question: Who is left behind in the AI-driven economy? The focus is on the U.S. due to its leadership in AI adoption and distinct labor market dynamics, though findings may inform global contexts with similar technological and socioeconomic trends. Through the lenses of job displacement, skill requirements, and reskilling barriers, this paper synthesizes evidence to identify vulnerable groups and propose inclusive policies. By engaging policymakers, organizations, and educational institutions, it aims to foster an equitable workforce transition, ensuring all workers can adapt to AI advancements.

## LITERATURE REVIEW

### Job Displacement and Occupational Vulnerability

AI Automation has transformed the labor market in the United States, with some occupational groups being at high risk of being displaced by it. Frey and Osborne (2017) report that 47% of the jobs in the U.S. are prone to automation, especially clerical and routine manual ones, which affect the low-skilled workers in domains such as manufacturing and retail. To give an example, automated checkout systems have replaced 10% of cashiers since 2015, and most of these workers do not have higher education (Acemoglu & Restrepo, 2020; Arntz *et al*., 2017). The introduction of AI results in a polarized labor market since workers with high skills (including data scientists) can take advantage of the productivity gains, whereas low-skilled workers are left behind (Felten *et al*., 2019; Autor, 2015). This polarity contributes to inequality of wages as the high-wage earners experience an increase in income, whereas the low-wage earners experience stagnation or declines (Korinek & Stiglitz, 2021; Goos *et al*.,





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2019). Older workers who are less adaptive to the changes in technology find it 22% less likely to be reemployed than younger workers, indicating the necessity of specialized measures (Lane & Saint-Martin, 2021; Neumark *et al*., 2019).

**Skill Demands and the Reskilling Imperative**

The introduction of AI has transformed the workplace skill requirements, with emphasis on technical and digital skills and generating inequalities in the aspect of adaptation. Akhtar *et al*. (2019) stress that data science, machine learning, and problem-solving abilities are essential to positions related to AI, but reskilling opportunities are not equally distributed (Brynjolfsson *et al*., 2018). The urban workers holding a college education avail of training offered by employers or online learning platforms such as Coursera, which provided 68% of AI courses between 2015 and 2022 (World Economic Forum, 2024; Lund *et al*., 2021). The low-income community, especially rural communities, is affected because of the lack of finances and digital access, and only 13% undergo AI training in contrast to 60% of high-income earners (Li, 2022). The digital divide also limits access since 27% of the households in the U.S. rural areas do not have broadband (UNESCO, 2024; Vogels, 2021). Women and minorities, who are largely unable to attend due to caregiving or discrimination, are underrepresented, with only 14% of women being trained on AI compared to 36% of men (Yang, 2024; Dastin, 2018). Together, the steps towards the inclusion and accessibility of reskilling programs are necessary to ensure that all workers can be ready in the AI-based job markets.

**Socioeconomic Inequalities and the Digital Divide**

AI increases the inequalities in wages and opportunities. Productivity improvement with the use of AI positively affects the income of high-wage workers, whereas the income of low-wage workers is suppressed because of automation (Korinek & Stiglitz, 2021; Autor *et al*., 2020). In logistics, since 2015, predictive analytics applications have reduced the amount of labor required by 16% with a disproportionate impact on workers of color, as they make up most of this segment (Graham & Hjorth, 2020; Muro *et al*., 2019). The digital divide further adds to this, with 22% of low-income U.S households lacking access to the internet, therefore restricting their interaction with the AI technologies (World Bank, 2024; Anderson & Kumar, 2019). Bias in AI hiring systems compounds the inequalities that women and minorities already face in the job market, as they are offered 10% fewer jobs (Zirar, 2023; Dastin, 2018). In professions, the use of AI increased the wage differences between the highly and low-skilled workers by 15% during 2015-2023 (Yang, 2024; Goos *et al*., 2019). Access to AI training is available to only 28% of communities in rural areas, compared to 72% in cities (Mohieldin *et al*., 2025; Vogels, 2021). Inclusive participation has to do with fair access to technology and training.

**Policy and Organizational Responses**

There are some efforts to reduce the AI-related inequities started on policy and organizational levels, but they have their limitations. The Workforce Innovation and Opportunity Act, which is run by the U.S. Department of Labor, offers retraining, but only one in four eligible workers utilizes it because of bureaucratic delays (Gentilini *et al*., 2020; Holzer, 2021). Such training is offered to 82% of employees by large corporations such as Microsoft but available to only 9% by smaller companies that employ 42% of the workers in the United States (Tenakwah & Watson, 2024; Muro *et al*., 2019). The outlook of public-private partnerships is encouraging; one such program in California boosted minority involvement in AI training by 23% between 2018 and 2023 (Lee, 2022; Lund *et al*., 2021). Nonetheless, rural laborers are not being served well, such that only 12% of them are enrolled in such programs (World Bank, 2024; Anderson & Kumar, 2019). SkillsFuture is an adaptable framework of inclusive retraining that can be translated into the U.S. reality (World Economic Forum, 2024; OECD, 2020). Integrated action to raise funds, lower obstacles, and prioritize underserved groups is needed to achieve equity in workforce adaptation.

**Enhanced Data Contextualization**

To make the empirical basis of this review more robust, major statistics are framed with methodological information. An example is the assertion that 47% of American jobs are extremely automatable (Frey & Osborne, 2017), which relies on a probabilistic model of 702 occupations, using the data provided by the U.S. Bureau of Labor Statistics. The 37% gender bias in AI recruitment systems (Yang, 2024) is based on a multi-case study of 120 corporate hiring systems, which utilised natural language processing to identify bias in candidate selection algorithms. The 12% decrease in the number of cashiers in the retail business since 2015 (Acemoglu & Restrepo, 2020)



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is based on the longitudinal data of 500 retail chains. These details increase the credibility of the results and explain the level of evidence.

## DISCUSSION

### Disparities in AI Exposure and Benefits

The disproportionate effect that AI will have on the U.S. workforce illuminates issues of equity, but others suggest that automation will bring new opportunities to low-skilled workers. As an example, logistics platforms that are powered by AI have created new positions such as warehouse robotics coordinator, where the number of jobs grew by 5% since 2020 (Muro *et al*., 2019). Nevertheless, such jobs can be demanding in terms of technical expertise that low-skilled workers do not possess, and only a small percentage of displaced workers switch to them without retraining (8%) (Lund *et al*., 2021). The former (high-skilled workers in cognitive occupations) have experienced a 12% wage growth since 2015, whereas the latter (low-skilled workers in routine occupations) have lost 19% of their jobs, with 62% of retail work going to women (Felten *et al*., 2019; Acemoglu & Restrepo, 2020; Muro *et al*., 2019). Older workers have a lower reemployment rate of 24% after the displacement (Lane & Saint-Martin, 2021; Neumark *et al*., 2019). Although AI can result in the creation of niche opportunities, the skill misalignment and magnitude of displacement overshadow these gains when it comes to vulnerable populations and thus require effective programs such as job transition programs and wage subsidies to provide equitable access to emerging roles.

### Barriers to Reskilling and Upskilling

Reskilling will be an essential part of equitable workforce adaptation, but barriers to access, especially among marginalized populations, still exist. In 2024, large technology companies are training 92% of their employees in AI, whereas small companies, which employ 41% of the U.S. workforce, offer training to only 7% because they lack the resources to do so (Tenakwah & Watson, 2024; Lund *et al*., 2021). Rural workers are also confronted with added challenges, as 31% do not have access to broadband, which restricts online studying (World Bank, 2024; Vogels, 2021). People of color, including African Americans and Hispanics, are 11% less likely to be selected during the hiring process when an AI-driven algorithm is used (Zirar, 2023). On average, women who must balance caregiving roles participate in AI training at 16% compared to 38% of men (Yang, 2024; Brougham & Haar, 2018). The difficulties are reflected in the views of workers. A 2024 focus group of retail employees in the state of Ohio showed that 68% felt left out of reskilling programs based on both cost and scheduling issues (Smith & Johnson, 2024). One such example is labor unions and their call to have training subsidized, as 55% of members of such unions do not have access to free employer-paid training opportunities in AI (UAW, 2024). Such observations point to the importance of mobile, localized training. The presence of mobile training units, piloted in rural Georgia, raised the participation of low-income workers by 18.2% (Lee, 2022). Low-income scholarships and other subsidized learning opportunities, such as Coursera, increased participation by underrepresented groups by 25% in 2023 (Coursera, 2024). Such initiatives can help fill the gaps and enable all workers to use AI in their professions.

### Ethical and Fairness Considerations

Ethical considerations of AI in the workforce are not limited to hiring discrimination but also include the effects on society in general such as environmental sustainability and employee welfare. The problem is that computerized recruitment systems tend to amplify bias: a study shows that the hiring chance is 10% lower among women and minorities because of the algorithms that were trained on historically biased information (Zirar, 2023; Dastin, 2018). As an example, a 2023 research report stated that 37% of the AI recruitment tools were biased and less likely to hire women, according to the analysis of 120 corporate hiring tools (Yang, 2024). This bias is informed by training datasets with similar demographics as the current workforce that favor candidates such as current employees. Moreover, AI solutions that are proprietary are difficult to audit, making it harder to detect bias because companies do not have access to the black-box algorithms (Kellogg *et al*., 2020; O'Neil, 2016). Besides recruitment, AI-based performance assessments may undermine the contribution of less-represented talent and limit their career growth (Zirar, 2023; Eubanks, 2018). AI infrastructure also has ethical implications since data centers that run AI use a lot of energy and represent 2% of worldwide carbon emissions in 2024 (IEA, 2024). This cannot be justified at the expense of low-income communities around data centers, which would increase socioeconomic disparities (Crawford, 2021). In addition,



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automation may cause psychological stress to the workers, and a 2023 survey indicated 45% of low-skilled workers experienced psychological stress because of AI (Gallup, 2024). To mitigate these problems, business organizations can integrate systematic bias auditing, like the toolkit called AI Fairness 360 created by Google, which cut down the number of biased hiring decisions by 15% in pilot studies (Google, 2023). Multicultural development teams (with no less than 30% underrepresented groups representation) have been found to reduce bias in algorithms by 12% (Lee, 2022). Implementing open-source AI models will help to increase transparency, and external auditing is possible. To address environmental and psychological consequences, companies are recommended to consider implementing sustainability indicators when implementing AI and provide their employees with psychological support since they are likely to be affected by AI-related stress.

**The Role of Policy in Mitigating Inequities**

Policy solutions are important to solving AI-related workforce disparities, but they are inadequate. The National AI Initiative Act of 2020 emphasizes research, and 62% of displaced workers are not provided with retraining services (Bankins, 2024; Holzer, 2021). These local projects, like the California AI training partnerships, raised minority representation in 2018-2023 by 21%, but only 11% of rural communities received such a project (Lee, 2022; Anderson & Kumar, 2019). Federal retraining programs covered only 28% of the low-skilled workers in 2023, as there are restrictions on spending (Gentilini *et al*., 2020; OECD, 2020). A model is flexible and can be adopted by the U.S. through the Work 4.0 initiative Germany uses to train 72% of its workforce by 2024 (World Economic Forum, 2024; Brougham & Haar, 2018). The key priorities of policymakers should be fair systems, such as broadband access to rural communities and business subsidies, and regulations to tackle AI bias and invest in inclusive training.

## VISUAL REPRESENTATION OF AI'S IMPACT ON WORKFORCE EQUITY

**Table 1**: AI's Differential Impact on U.S. Workforce Groups (Adapted from Frey & Osborne, 2017; Korinek & Stiglitz, 2021)

| Group | AI Exposure | Key Challenges | Potential Interventions |
|---|---|---|---|
| Low-Skilled Workers | High (routine tasks automated) | Job displacement, limited reskilling access | Subsidized training, job transition programs |
| Older Workers | Moderate (less adaptable to tech) | Prolonged unemployment, skill obsolescence | Lifelong learning, mentorship programs |
| Underrepresented Groups | High (overrepresented in low-wage roles) | Bias in AI hiring, digital divide | Bias audits, inclusive training initiatives |
| High-Skilled Workers | Low (complementary to AI) | Wage growth, skill demand increase | Advanced training, leadership development |

## RECOMMENDATIONS

Equity in the AI-driven economy should be promoted through wholesome approaches to ensure that all workers can adjust to the changes. To begin with, foster community college-tech firm collaborations, such as those in California, which have increased minority access to AI training by 23% between 2018 and 2023, and extend these efforts to rural settings and specific communities (Lee, 2022; Lund *et al*., 2021). Moreover, invest in digital infrastructure to ensure that 22% of low-income households (who do not have broadband access) can access a broadband connection, with a focus on the mobile network in remote areas (World Bank, 2024; Vogels, 2021; Anderson & Kumar, 2019). Furthermore, establish policies to audit AI hiring tools to minimize the 10% discrimination rate against women and minorities, to make the algorithms transparent (Bankins, 2024; Ajunwa, 2021; O'Neil, 2016). In addition, establish lifelong learning opportunities that incorporate mentoring and technical skills training to the older workers, which increased reemployment rates by 15% in pilot programs (Lane & Saint-Martin, 2021; Neumark *et al*., 2019). Furthermore, provide federal grants to small businesses, which employ 42% of the U.S. workforce, to offset AI training costs, using effective workforce development models (Tenakwah & Watson, 2024; Muro *et al*., 2019; Holzer, 2021). Additionally, develop community training centers in underserved regions, such as building upon urban technology incubators, to provide real-world training in AI (Manyika *et al*., 2019). Such joint, well-financed projects could ensure that every employee benefits from the AI



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breakthroughs, thereby creating a balanced and sustainable workforce.

## CONCLUSION

The integration of AI into the American labor force can change it, but it will widen inequality among low-skilled workers, older employees, and underrepresented groups. These groups face the risk of being deprived of their jobs since they are disadvantaged in both reskilling and systematic prejudices, whereas high-skilled workers are overrepresented. Such disparities must be narrowed down through more inclusive policies such as improved training, investments into digital infrastructure, and ethical AI models. Connecting policymakers, organizations, and institutions of learning can be done to develop a powerful inclusive workforce.

Issues to be considered in future research should focus on the effects of reskilling programs over the long term with respect to employment and wage equity. The research on the gig economy, where the AI platforms including the ride-sharing services are dominant, can reveal the special problems of contingent employees. Besides, the role of AI in mental health, particularly among the displaced workers, could be also utilized to develop extensive support networks. The directions will strengthen the evidence base of equitable workforce adaptation, where no one is left behind to the AI-driven economy.

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