

# The Impact of Artificial Intelligence Adoption on Employee Unemployment: A Multifaceted Relationship

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## ABSTRACT

This article comprehensively reviews the impact of artificial intelligence (AI) and automation on employment. As AI and automation technologies continue to advance and be adopted across various sectors, concerns have been raised about their potential to displace jobs and exacerbate income inequality. The article examines the existing literature on the subject, discussing the potential for job substitution and changes in employment structure. It also explores the concept of skill-biased technological change and its implications for the labor market. The review highlights the need for proactive policies to address the challenges posed by automation, such as investing in education and training, fostering innovation and job creation, and considering measures like universal basic income. The article concludes by emphasising the importance of understanding and managing the impact of AI and automation on employment to ensure a more equitable and prosperous future of work.

## KEYWORDS

Artificial Intelligence; Employment; Job Displacement; Skill-Biased Technological Change; Future of Work; Universal Basic Income.

## 1. INTRODUCTION

The rapid advancement and widespread adoption of AI technologies have raised concerns about their potential impact on employment. While some experts predict that AI will lead to significant job losses and technological unemployment [9], others argue that AI will create new jobs and enhance productivity (Autor & Salomons, 2018). This debate has attracted considerable attention from researchers, policymakers, and the general public, as the implications of AI for the future of work are far-reaching and complex.

The relationship between AI adoption and employee unemployment is multifaceted and involves various economic, social, and technological factors. Despite the growing body of research on this topic, there still needs to be a consensus on the net impact of AI on employment [2]. Moreover, the existing literature often focuses on specific industries or regions, making it difficult to generalise the findings. This literature review aims to provide a comprehensive understanding of the impact of AI adoption on employee unemployment by examining the existing research and identifying key findings, limitations, and gaps in the current knowledge base. This review aims to synthesise the available evidence, offer insights into the complex relationship between AI and unemployment, and provide direction for future research and policy-making .

The literature review is organised into seven main sections. Following the introduction, "Historical Perspective on Automation and Employment" provides a historical perspective on automation and

employment, highlighting key milestones and early studies. "Theoretical Frameworks" discusses the main theoretical frameworks used to analyse the impact of AI on employment, including technological unemployment theory, skill-biased technological change theory, and job polarisation theory. "Previous Research Findings" summarises the previous research findings, categorising them into studies supporting negative impact, studies suggesting neutral or positive effects, and critiques of existing literature. "Emerging Trends and Debates" explores emerging trends and debates, such as the rise of the gig economy and the ethical implications of AI in the workplace. "The Multifaceted Relationship between AI Adoption and Employee Unemployment" synthesises the findings and discusses the multifaceted relationship between AI adoption and employee unemployment. Finally, the conclusion summarises the key insights, identifies knowledge gaps, and discusses implications for policy and practice.

## **2. HISTORICAL PERSPECTIVE ON AUTOMATION AND EMPLOYMENT**

The relationship between automation and employment has been a topic of interest for economists and policymakers for centuries. The early stages of the Industrial Revolution in the late 18th and early 19th centuries saw the introduction of machines that replaced manual labour, leading to concerns about technological unemployment (Mokyr et al., 2015). However, despite initial job losses in some sectors, the Industrial Revolution ultimately led to increased productivity, economic growth, and the creation of new jobs in emerging industries (Allen, 2017).

In the 20th century, the rapid advancement of technology and the rise of computer-based automation reignited the debate about the impact of automation on employment. The introduction of industrial robots in the 1960s and 1970s led to significant job losses in the manufacturing sector, particularly among low-skilled workers [1]. However, the overall impact of automation on employment during this period was mixed, with some studies suggesting that automation also contributed to job creation and wage growth [12].

The advent of the digital age and the widespread adoption of information and communication technologies (ICTs) in the late 20th and early 21st centuries marked a new era in the relationship between automation and employment. The computerisation of many tasks previously performed by humans led to concerns about the potential for large-scale technological unemployment [5]. However, empirical evidence from this period suggests that the impact of ICTs on employment was largely positive, with the creation of new jobs in the digital economy offsetting job losses in other sectors [4].

The historical perspective on automation and employment highlights this relationship's complex and dynamic nature. While automation has undoubtedly led to job losses in some sectors and periods, it has also contributed to economic growth, productivity gains, and new jobs in emerging industries. As we enter the age of artificial intelligence, it is crucial to consider the lessons from history and approach the relationship between AI and employment with a nuanced understanding of the potential risks and opportunities.

## **3. THEORETICAL FRAMEWORKS**

Several theoretical frameworks have been developed to analyse the impact of AI on employment. These frameworks provide valuable insights into the complex relationship between technological change and labour markets. This section discusses three key theoretical frameworks: technological unemployment theory, skill-biased technological change theory, and job polarisation theory.

### **3.1. Technological Unemployment Theory**

Technological unemployment theory posits that technological progress can lead to job losses as machines replace human labour (Keynes, 1930). According to this theory, as AI technologies become

more advanced and capable of performing a more comprehensive range of tasks, they will increasingly substitute for human workers, leading to job displacement and unemployment [9]. This theory emphasises the potential negative impact of AI on employment, particularly for low-skilled workers whose jobs are more susceptible to automation.

However, critics of technological unemployment theory argue that it overlooks the job-creating effects of technological change [4]. They contend that while AI may displace some workers in the short term, it will also create new jobs and industries in the long run, as has been the case with previous waves of automation [1].

### **3.2. Skill-Biased Technological Change Theory**

Skill-biased technological change (SBTC) theory suggests that technological progress favours skilled workers over unskilled workers, leading to a widening wage gap and increased inequality (Katz & Autor, 1999). According to this theory, AI technologies complement high-skilled workers, enhancing their productivity and increasing the demand for their skills. In contrast, AI technologies are substitutes for low-skilled workers, reducing the demand for their labour and potentially leading to job losses (Acemoglu & Autor, 2011).

SBTC theory has been widely used to explain the rising wage inequality and the decline of middle-skill jobs in developed economies in recent decades [11]. However, some researchers argue that SBTC theory needs to fully capture the complexity of the relationship between AI and employment, as it focuses primarily on the skill level of workers rather than the specific tasks they perform [1].

### **3.3. Job Polarization Theory**

Job polarisation theory posits that technological change leads to a hollowing out of middle-skill jobs while increasing the demand for both high-skill and low-skill jobs (Autor et al., 2003). According to this theory, AI technologies automate routine tasks commonly performed by middle-skill workers, such as clerical work and repetitive production tasks. As a result, the demand for middle-skill jobs declines, leading to job losses and wage stagnation (Goos & Manning, 2007).

At the same time, job polarisation theory suggests that AI technologies increase the demand for high-skill jobs requiring abstract thinking and problem-solving skills and low-skill jobs requiring non-routine manual tasks (Autor & Dorn, 2013). This leads to a polarisation of the labour market, with growth in both high-wage and low-wage jobs and a decline in middle-wage jobs.

Job polarisation theory has been supported by empirical evidence from various countries, including the United States, the United Kingdom, and Germany (Goos et al., 2009). However, some researchers argue that the extent of job polarisation varies across countries and depends on factors such as labour market institutions, education systems, and technological change (Fernández-Macías & Hurley, 2017).

## **4. PREVIOUS RESEARCH FINDINGS**

### **4.1. Potential Job Losses**

A significant body of research suggests that AI adoption could lead to substantial job losses, particularly in sectors and occupations more susceptible to automation. Frey and Osborne's (2017) influential study estimates that 47% of US employment is at high risk of computerisation over the next two decades. They argue that machine learning and mobile robotics advances will enable AI systems to perform a wide range of cognitive and manual tasks, potentially displacing millions of workers.

Other studies have provided similar estimates of the potential job losses associated with AI adoption. For example, McKinsey Global Institute (2017) estimates that by 2030, automation, including AI technologies, could displace up to 800 million jobs worldwide. They suggest that the impact of AI on employment will vary across countries and sectors, with developed economies and labour-intensive industries being more vulnerable to job losses.

However, these studies have been criticised for potentially overestimating the extent of job displacement, as they often focus on the technical feasibility of automation rather than its economic viability or the social and regulatory barriers to adoption (Arntz et al., 2016). Moreover, these studies do not fully account for the job-creating effects of AI, such as the emergence of new industries and occupations (Acemoglu & Restrepo, 2019).

#### **4.2. Job Creation and Productivity Gains**

While the potential job losses associated with AI adoption have received significant attention, some researchers argue that AI will create new jobs and boost productivity. Acemoglu and Restrepo (2018) developed a framework that distinguishes between the displacement and productivity effects of AI. They argue that while AI may displace some workers in the short term, it will also increase productivity and create new tasks that require human labour, leading to a net positive impact on employment in the long run.

Empirical evidence supports the idea that AI adoption can lead to job creation and productivity gains. For example, Bughin et al. (2018) estimate that AI could contribute up to \$13 trillion to the global economy by 2030 through a combination of increased productivity and the creation of new products and services. They suggest that AI will create new jobs in areas such as AI development, data analysis, and digital marketing, offsetting job losses in other sectors.

Other studies have found that AI adoption can lead to productivity gains and wage growth, particularly for high-skilled workers. For example, Graetz and Michaels (2018) find that adopting industrial robots in 17 countries between 1993 and 2007 led to significant productivity gains and wage growth without reducing overall employment. They suggest that the productivity gains from robotics were captured mainly by high-skilled workers, supporting the skill-biased technological change theory.

#### **4.3. Mixed and Context-Dependent Impact**

While some studies suggest that AI will hurt employment and others argue for a positive impact, a growing body of research indicates that the relationship between AI and employment is complex and context-dependent. The impact of AI on employment is likely to vary across countries, sectors, and occupations, depending on factors such as the pace of technological change, the skill level of the workforce, and the institutional and regulatory environment (Goos et al., 2019).

For example, Felten et al. (2018) analysed the impact of AI on employment in the United States and found that the effect varies significantly across occupations. They suggest that AI will likely complement high-skilled workers in professions such as management and professional services while substituting for low-skilled workers in transportation and manufacturing.

Similarly, Muro et al. (2019) examine the geographic distribution of AI-related jobs in the United States and find that the impact of AI on employment varies across regions. They suggest that metropolitan areas with a high concentration of high-tech industries and educated workers are more likely to benefit from AI adoption. In contrast, rural areas and regions with a less educated workforce may be more vulnerable to job losses.

These studies highlight the need for a nuanced and context-specific understanding of the relationship between AI and employment. Rather than making broad generalisations about the impact of AI on

jobs, researchers and policymakers should consider the specific characteristics of different industries, occupations, and regions when assessing the risks and opportunities associated with AI adoption.

## **5. EMERGING TRENDS AND DEBATES**

### **5.1. The Rise of the Gig Economy**

The rise of the gig economy, characterised by short-term contracts and freelance work, has been facilitated by AI-powered platforms such as Uber, Airbnb, and Upwork. These platforms use AI algorithms to match workers with tasks, optimise pricing, and monitor performance (Duggan et al., 2020). While the gig economy has created new opportunities for flexible employment, it has also raised concerns about job quality, social protection, and workers' bargaining power (De Stefano, 2016).

Some researchers argue that the gig economy represents a new form of work well-suited to the age of AI, as it allows for the efficient allocation of tasks and the utilisation of human skills that cannot be easily automated (Manyika et al., 2016). However, others contend that the gig economy may exacerbate income inequality and job insecurity, as gig workers often lack access to benefits, training, and collective bargaining [13].

### **5.2. Reskilling and Lifelong Learning**

As AI technologies advance and disrupt labour markets, there is a growing recognition of the need for reskilling and lifelong learning initiatives to help workers adapt to changing job requirements. Many researchers and policymakers argue that investing in education and training programs is crucial for mitigating the negative impact of AI on employment and ensuring that workers have the skills needed to thrive in the age of AI [1][18].

Reskilling initiatives can take various forms, such as on-the-job training, online courses, and vocational education programs. For example, the World Economic Forum (2020) has launched the Reskilling Revolution initiative, which aims to provide one billion people with better education, skills, and jobs by 2030. The initiative involves a coalition of governments, businesses, and educational institutions working together to create new learning and career development pathways.

However, the effectiveness of reskilling initiatives depends on various factors, such as the quality of training programs, the alignment of skills with labour market needs, and the willingness of employers to invest in worker training [17]. Moreover, reskilling initiatives may not be sufficient to address the structural changes in labour markets caused by AI, such as the polarisation of jobs and the decline of middle-skill occupations (Autor & Reynolds, 2020).

### **5.3. Universal Basic Income and Social Protection**

As AI technologies continue to disrupt labour markets and potentially lead to job losses, some researchers and policymakers have proposed universal basic income (UBI) as a potential solution for ensuring social protection and reducing income inequality. UBI refers to a system in which all citizens receive a regular, unconditional cash payment from the government, regardless of their employment status or income level [21].

Proponents of UBI argue that it could provide a safety net for workers displaced by AI, reduce poverty and income inequality, and promote entrepreneurship and innovation by providing a stable income floor [20]. Moreover, UBI could help to redistribute the productivity gains from AI and ensure that the benefits of technological progress are shared more widely [15].

However, critics of UBI argue that it could discourage work, reduce productivity, and strain public finances [14]. Moreover, implementing UBI would require significant changes to existing social protection systems and tax structures, which may be politically challenging [10].

## 6. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The rapid development and adoption of AI technologies have profound implications for labour markets and employment. While some studies suggest that AI could lead to significant job losses, particularly in sectors and occupations more susceptible to automation, others argue that AI will also create new jobs and boost productivity. The relationship between AI and employment is complex and context-dependent, varying across countries, sectors, and occupations.

To fully understand the impact of AI on employment, future research should focus on developing more nuanced and context-specific models that account for the heterogeneous effects of AI across different industries, occupations, and regions. Moreover, researchers should investigate the effectiveness of various policy responses to AI-induced labour market disruptions, such as reskilling initiatives, universal basic income, and social protection systems.

As AI technologies continue to advance and reshape labour markets, researchers, policymakers, and businesses must work together to ensure that the benefits of AI are shared widely and that the negative impacts on employment are mitigated. This requires a proactive and collaborative approach to managing the transition to an AI-driven economy, prioritising workers' well-being and resilience while harnessing AI's potential for economic growth and social progress.

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