Croatian Regional Development Journal | Vol. 5 No. 2 | 2024

Economic Theory and Artificial Intelligence: A Cross-model Perspective on Labour Market Dynamics

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Abstract

This study examines the relationship between labour market changes and artificial intelligence, utilising Romer's Endogenous growth theory, Schumpeter's Creative destruction, Solow's Growth model and Becker's Human capital theory as theoretical frameworks. The purpose of this research is to clarify the multifaceted impacts of artificial intelligence on economic growth, workforce adjustment and the emergence of novel employment trends, focusing specifically on job losses and gains, wage inequalities, and changing skill requirements. Using a structured literature review methodology, the economic implications of artificial intelligence in the labour market were systematically analysed and synthesised. The results suggest that although artificial intelligence significantly enhances productivity and innovation, it has a complex effect on the labour market, causing employment gains in technologically sophisticated industries and losses in sectors prone to automation. The study emphasises strategic policy interventions and pedagogical reforms that maximise the economic benefits of AI while minimising its disruptive effects on employment. Proponents of such policies argue that by cultivating a workforce that is resilient and capable of adjusting to changes driven by artificial intelligence, they can effectively mitigate inequality and safeguard economic stability.

Keywords: artificial intelligence; AI; labour market dynamics; economic theory
Paper type: Research article

Received: Mar 4, 2024
Accepted: Jul 30, 2024

DOI: 10.2478/crdj-2024-0008

Introduction

The emergence of artificial intelligence (AI) marks a crucial point in the development of labour markets globally. AI technologies are rapidly advancing, presenting significant benefits but also challenges for the world's economies (Autor, 2015). This research aims to investigate the complex relationship between advancements in AI and shifts in the labour market, analysed within the context of traditional and modern economic theories and models. This diversity of AI technologies (from machine learning algorithms optimising supply chains to AI-driven analytics forecasting market trends) implies that the effects of AI on the labour market and the economy are not uniform but vary across sectors, job types, and geographical regions. The dynamics introduced by AI also challenge conventional economic metrics and models. Traditional measures may not fully capture the nuances of AI-driven efficiency gains (Furman & Seamans, 2019).

The widespread adoption of AI in different industries is causing a notable change in the employment market where automation is displacing jobs, especially in routine and manual sectors (Acemoglu & Restrepo, 2017). Routine, manual tasks are being automated, resulting in job losses. AI has a significant impact on manufacturing labour market dynamics, altering job patterns, skill requirements, wage structures, and the entire economic environment (Lane & Saint-Martin, 2021). AI is transforming this industry by automating routine and manual processes that were once vital to manufacturing employment (Porter & Heppelmann, 2015; Pejić Bach et al., 2023). This automation raises concerns about job displacement for tasks that are susceptible to machine replacement, but it also creates a demand for new skill sets that complement AI technologies.

The 2018 study on AI's influence on the labour market by Acemoglu and Restrepo (2018) highlights a complicated relationship between AI, labour demand, and wages. High-skilled jobs are also affected; however, this transition is also generating new job prospects that necessitate sophisticated cognitive abilities and digital proficiency. Additionally, the polarisation trend has important implications for wage structures (Acemoglu & Autor, 2011). The growth in high-skill jobs, which typically offer higher wages, and the stability of low-skill jobs, often associated with lower wages, can lead to widening wage disparities. This trend can exacerbate existing income inequalities, raising concerns about the equitable distribution of economic gains from AI and automation. This situation has both positive and negative effects, leading to important considerations regarding the future of employment, the disparity in income, and the need for governmental actions to oversee the shift towards a more AI-focused economy. This paper explores how AI-driven advancements may alter job markets, highlighting the necessity for a workforce that is flexible, skilled in technology, and committed to ongoing education to succeed in this changing environment. People can be better prepared for the shifting nature of the labour market by investing in their education (Aoun, 2017).

The goal of this research is to methodically analyse and comprehend the influence of AI on labour market dynamics using recognized economic theories. This research intends to provide a complete perspective on how AI is transforming the global labour market by including ideas from Romer (Romer, 1990), Schumpeter (Schumpeter, 2013), Solow (Solow, 1957), and Becker (Becker, 2009).

This study utilises a secondary research approach, a Structured literature review (SLR), to systematically collect, evaluate, and integrate current research on the effects of AI on labour market dynamics. This process includes the precise determination of search terms, databases, and criteria for inclusion or exclusion. This paper will present conducted research to comprehend how AI is transforming employment scenarios, work dynamics and the wider economic consequences. The paper explores economic theory to provide a detailed analysis of how artificial intelligence (AI) affects labour market dynamics. Romer's Endogenous growth theory (Romer, 1990) suggests that internal causes like technical advancements and human knowledge mostly propel economic progress. This research questions emphasise the importance of AI in boosting productivity and promoting economic growth.

The analysis also focuses on Schumpeter's theory of Creative destruction (Schumpeter, 2013) in relation to the disruptive impact of AI. This model can imply that although AI may make some jobs unnecessary, it also creates opportunities for new sectors and jobs. The Solow Growth model (Solow, 1957) is reviewed to analyse the impact of AI on important factors of growth such as labour, capital, and technology, highlighting AI's role in enhancing economic efficiency and productivity. Becker's Human capital theory (Becker, 2009) is essential for comprehending how AI affects the workforce, emphasising the significance of education and skill enhancement in the era of automation. As Bessen (2018) states, automation is altering the traditional understanding of labour and capital. The infusion of automated processes in industries has led to a reconfiguration of job roles and a recalibration of the skills that are valued in the labour market. While automation has historically been seen as a tool to augment human labour, the advent of sophisticated AI systems raises the prospect of replacing human labour in an unprecedented way. These economic theories offer a strong structure for examining the many impacts of AI on the labour market, connecting conventional economic concepts with the modern digital revolution. The paper will explore how AI technologies are changing employment patterns, skill requirements, and workplace structures in the labour market.

Methodology

For the purpose of research, a detailed analysis of the academic literature is conducted with a focus on the recognized economic theories. A comprehensive examination of empirical and theoretical studies investigating the effects of these models on labour market dynamics, especially considering emerging AI technology, has been conducted. This approach involves selecting and combining relevant publications to get insights into the theoretical foundations of each model and their practical consequences for the labour market. The literature review encompasses several study themes, such as the impacts of AI on low-skill and high-skill jobs, employment trends, job creation, workforce education, the influence of government policies on labour market outcomes and the adaptability and flexibility of the labour market. Conclusions of this paper are reached by critically evaluating the gathered literature, pinpointing similar themes, differing perspectives, and areas where the existing knowledge of AI's influence on labour market dynamics is lacking.

The research questions are outlined below to effectively conduct a structured literature review and ensure a cohesive analysis. Based on this, the research questions are as follows:

- RQ1. What is the impact of AI on job creation/destruction across different economic sectors?
- RQ2. What are the potential consequences of the changes in the labour market caused by AI-driven advancements for economic theories related to growth, productivity, and human capital?

Table 1 contains the elements of a structured literature review like search terms, databases, themes, and criteria.

The primary objective of this initial search was to encompass a wide range of literature that explores the dynamic relation between technological advancements, innovation, and patterns in employment. The search phrases were carefully chosen to cover a broad variety of conversations in the field. They included combinations such as "AI and labour market dynamics" and "technological innovation in employment," among others, to ensure a thorough exploration of the topic.

During the construction of this systematic literature review, an initial investigation was carried out using various databases such as JSTOR, ScienceDirect, Google Scholar, and specific economic and business journals. A wide range of search terms related to the influence of AI and innovation on labour markets were used.

The framework for a systematic review of the impact of AI and technological innovation on the labour market focuses on several key themes. It examines how technological advancements affect low-skill and high-skill jobs differently, their general impact on employment and job creation, and the necessary changes in workforce education. The review also evaluates government policies and the adaptability and flexibility of the labour market in response to these changes.

Only articles written in English that specifically study the effects of AI, innovation, or technological innovation on the labour market are included. Studies older than 30 years, except for those providing foundational economic theory and general technology reviews without a specific focus on AI or innovation, are excluded.

The quality assessment ensures that the studies are relevant to the research questions, methodologically rigorous, and from credible sources.

Table 1

Structured literature review elements

Elements	Description
Search terms	• "AI and labour market dynamics" • "(AI OR innovation) impact on employment" • "Economic theories of (AI OR innovation)" • "AI and job displacement" • "AI and job creation" • "Innovation and labour market" • "Technological innovation in employment"
Databases searched	JSTOR, ScienceDirect, Google Scholar, and specific economic and business journals.
Themes of interest	Impact on low-skill and high-skill jobs, general impact on jobs, job creation, education of the workforce, government policies, adaptability, and flexibility of the labour market.
Inclusion criteria	Articles written in the English language and studies that specifically examine the effects of AI, innovation, or technological innovation on the labour market.
Exclusion criteria	Studies older than 30 years (except for economic theory), general technology reviews without a specific focus on AI or innovation.
Quality assessment	Relevance to research questions, methodological rigour, and credibility of the source.

Source: Author's work (2024)

The initial search produced a significant number of papers, from which a more focused manual selection was made using tight criteria for inclusion, such as limiting the language to English and focusing on the specific impacts of AI or technological advancement on the labour market. Excluded from consideration were papers that did not specifically address the junction of AI or innovation with labour markets, as well as broad technology evaluations that did not have a strong focus on the implications for the labour market. In addition, research that was more than 30 years old was typically not included unless it clearly related to fundamental economic ideas that were fundamental to the study.

A total of 192 articles were initially identified using this method, all of which satisfied the basic search parameters. Every article was subjected to a comprehensive quality evaluation that specifically considered its pertinence to the research questions, the strength of its methodology, and the reliability of its source. Only the most relevant were picked for further examination through this rigorous screening. Following a thorough assessment, the quantity of papers that underwent comprehensive scrutiny and were ultimately incorporated into the final analysis was reduced to 105 (presented in Appendix A).

The papers presented many viewpoints and information on the ways in which AI, innovation and technological advancements are transforming labour markets, impacting the creation and displacement of jobs, altering skill needs, and affecting the wider economic consequences of these changes. The chosen studies collectively emphasise important patterns and offer a strong foundation for comprehending the various effects of AI and innovation on labour market dynamics. These effects are thoroughly examined in the following sections of the review. In the next chapter, a detailed examination of the outcomes derived from the structured literature review is presented. Results chapter is divided in two subchapters: Analysis (synthesis of findings from literature review) and Conclusions (presentation of key components of literature review).

Results

Overview

Table 3 summarizes key components of each analysed economic theory. Each theory offers a unique perspective for examining the impacts of AI's integration, covering aspects such as advancements in innovation and productivity, displacement of jobs and changing requirements for skills and education.

Endogenous growth theory (Romer, 1990) emphasizes the capacity of AI to greatly enhance productivity and economic growth via fostering creativity. Creative destruction advances the concept where AI displaces jobs in some industries while creating new ones in others, highlighting the dynamic nature of technological progress (Schumpeter, 2013). Solow's model (Solow, 1957) places AI in the context of economic growth, indicating diverse effects on different sectors but generally favourable effects on efficiency and output. Human capital theory (Becker, 2009) emphasizes the crucial need of education and skill enhancement in response to the changing requirements of an economy influenced by AI, highlighting the need for human capital development. Essentially, these theoretical perspectives emphasize that AI presents significant economic development and job creation possibilities, but also brings issues related to displacement and changing skill demands in the labour market. For AI to be successfully incorporated into the economy, it is crucial to make strategic investments in research, implement adaptive policies to assist with labour market changes and prioritize education and training (Brundage et al., 2016). Proactive steps are essential for maximizing the benefits of AI, guaranteeing economic resilience, and promoting an inclusive distribution of its advantages.

Table 2

Economic theories and perspective on AI impact on labour market dynamics

Economic theory	Key components	Findings
Endogenous growth theory (Romer, 1990)	Innovation and technology adoption as drivers of growth	Potential for enhanced productivity and economic expansion through AI-driven innovation
Creative destruction (Schumpeter, 2013)	Technological change leading to job displacement and the creation of new industries	Dual effect of AI: job displacement in some sectors and creation of new opportunities in others
Solow's growth model (1957)	Contributions of capital, labour, and technology to economic growth and impact of AI on productivity	AI is a pivotal factor in boosting economic efficiency and output, with varying effects across sectors.
Human capital theory (Becker, 2009)	Impact of AI on the quality of the labour force and the necessity of re-skilling and education	Emphasises the importance of education and skill development in the age of automation

Source: Author's work (2024)

Endogenous growth theory

The Endogenous growth theory proposed by Paul Romer (Romer, 1990) places a strong emphasis on the role that technical innovation plays as a main driver of economic growth over the long run (Romer, 1990). Romer's theory, when applied to the field of AI, proposes that there is more to AI than merely an increase in productivity. Rather, it is a key catalyst for new types of economic development and progress. The capacity of AI to handle and analyse data, automate complicated activities, and promote innovation across a wide range of industries places it in a position to be an essential component of the endogenous growth framework. Taking this viewpoint into consideration highlights the potential for AI to sustain a cycle of innovation, investment, and greater economic output. In addition, Romer's theory (Romer, 1990) proposes that investments in AI research and development might result in increasing returns, in contrast to investments in traditional capital. AI technologies are non-rivalrous and scalable, meaning that they may be utilised across a wide range of industries and sectors, hence increasing their impact on economic growth. Not only can the implementation of AI in fields such as manufacturing, education, and finance result in increased productivity, but it also paves the way for new opportunities for innovation and market expansion. One other implication of Romer's theory (Romer, 1990) is that discoveries led by AI might result in new types of intellectual property and business models, which in turn stimulates additional economic growth. As an illustration, AI algorithms and data science models have developed into valuable assets, which has led to the development of new sectors centred on data science and AI-based services.

The theory places a strong focus on knowledge and ideas as the primary drivers of sustainable economic progress, and AI serves as a vital enabler in the process of achieving this goal (Agrawal et al., 2018).

Creative destruction

The term "creative destruction" was used by Joseph Schumpeter to characterise the process by which new technologies disrupt and replace older ones, hence promoting economic growth (Schumpeter, 2013). AI is a prime example of this process since it “upsets” old business models and industry practices, hence paving the way for new ideas and approaches to market composition. Schumpeter’s viewpoint emphasises the dual nature of AI (Schumpeter, 2013), which is both a disruptor and a creator. It suggests that the long-term economic benefits of AI-driven change outweigh the short-term disruptions that they produce. Schumpeter's theory (Schumpeter, 2013) also suggests that the creative destruction brought about by AI has the potential to bring about substantial societal and economic benefits. As an illustration, the growing prevalence of AI in the retail industry has resulted in the transformation of conventional shopping experiences, which in turn has led to the development of online commerce and digital marketplaces (Nathan et al., 2018). This transition, even though it is disruptive, prepares the way for better efficiency, decreased inconvenience for customers, and new business models. The disruptive influence that AI has had on established businesses might be considered a necessary step for the revitalisation and innovation of the economy. Over time, this results in the development of more effective business processes, the production of new industries, and an economic landscape that is more dynamic (Brynjolfsson et al., 2014). This is in line with Schumpeter's concept (Schumpeter, 2013) of the ongoing evolution and advancement of the economy.

Solow's growth model

An understanding of how AI affects productivity can be gained using Robert Solow's growth model, which ties long-term economic growth to technical progress (Solow, 1957). Increasing productivity is a critical factor in determining economic growth, and Solow's model shows that AI, which is a form of technical advancement, makes a considerable contribution to productivity gains. The purpose of this model is to emphasise the role that AI plays not only in improving the efficiency of processes that are already in place but also in enabling new production alternatives and economic activities. When Solow's model (Solow, 1957) is applied to AI, it becomes clear that AI has the potential to make a considerable contribution to the "Solow residual." This refers to the portion of economic growth that is not accounted for by traditional inputs such as labour and capital. There is the potential for significant productivity improvements to result from the role that AI plays in automating processes and enabling data-driven decision-making. These gains are essential to increases in overall economic production and living standards. As a result of applying Solow's concept

(Solow, 1957) to AI, it is possible that the benefits of productivity gains caused by AI would not be immediately apparent in economic production. This is a phenomenon known as the "Solow paradox." On the other hand, as time passes and AI technologies get more integrated and their utilisation becomes more efficient across many industries, the true influence that these technologies have on productivity and economic growth becomes more apparent (Brynjolfsson et al., 2000). This reflects Solow's insights into the nature of technological advancement (Solow, 1957).

Human capital theory

When it comes to comprehending the influence that AI will have on the labour market, Gary Becker's Human capital theory, which emphasises the significance of investing in education and training for the purpose of fostering economic growth, is particularly appropriate (Becker, 2009). Becker's theory highlights the necessity for education and training systems to evolve in response to the changing nature of work and the skills that are required in the labour market because of the impact of AI (Becker, 2009). Specifically, this entails modifying educational programs so that they incorporate AI literacy, boosting education in STEM fields, and placing an emphasis on the development of skills that are complementary to AI technologies. In the face of advances in AI, Becker's thesis emphasises the importance of developing human capital in an adaptable way (Becker, 2009). The demand for continual skill adaptation and lifetime learning is growing because of the impact that AI is having on employment needs. This viewpoint highlights the significance of policy measures and educational reforms that concentrate on the development of qualities that are complementary to AI. These talents include critical thinking, creativity, and emotional intelligence. In accordance with Becker's theory (Becker, 2009), the always-developing characteristics of AI technology call for a comparable development in human capital. To effectively collaborate with AI systems, it is necessary to not only acquire new technical skills but also build adaptability, problem-solving abilities, and emotional intelligence. This evolution is not just about obtaining new technical capabilities. As a means of educating individuals for a future in which AI will be an essential component of the labour force, the theory emphasises the significance of an educational system that is adaptable and sensitive to the shifting requirements of an economy driven by AI (Chen et al., 2020).

Economic theories and perspective on AI's impact on labour market dynamics

Table 3. summarises key perspectives from analysed economic theories on key topics. The models provide a systematic framework for comprehending the many impacts of AI on job displacement, creation, and the changing requirements of the workforce. Analysing the influence on low-skilled and high-skilled jobs, overall employment effects, new job creation dynamics, the importance of education, government policy implications and the adaptability of the labour.

Table 3

Economic theories and perspective on AI's impact on labour market dynamics

Perspective	Endogenous growth theory (Romer)	Creative destruction (Schumpeter)	Solow's growth model	Human capital theory (Becker)
Impact on low-skill jobs	Potential displacement due to automation and technology adoption	High risk of displacement, but also opportunities in emerging sectors	Displacement is likely, but productivity gains could lead to overall economic growth	Emphasises the need for re-skilling and continuing education
Impact on high-skill jobs	Enhanced opportunities through innovation and economic expansion	Opportunities for growth in new industries and entrepreneurial ventures	Less impact due to the complementarity of AI with high-skill tasks	Critical for driving innovation and sustaining economic growth
General impact on jobs	Shift towards more technologically advanced, innovative job roles	Destruction and creation cycle leading to a dynamic job market	Varies by sectors where overall productivity gains could lead to job growth	Increased demand for high-quality labour and specialized skills
Job creation	Driven by innovation and new technology markets	Emergence of new industries and business models	Dependent on the adoption rate of AI technologies	Linked to the development of new skills and competencies
Education of workforce	Need for ongoing learning and adaptation to technological advancements	Focus on entrepreneurship and innovation skills	Technical and vocational training to meet changing job requirements	Emphasis on lifelong learning and adaptability
Government policies	Support for innovation and technology development	Regulations to manage the transition and support displaced workers	Investment in infrastructure and education for a skilled workforce	Policies to foster human capital development and labour market flexibility
Adaptability and flexibility of the labour market	Emphasises the role of innovation in creating flexible job markets capable of adapting to changes	Highlights the cyclical nature of job creation and destruction, requiring a labour market that can quickly adapt	Importance of economic structure and policy in facilitating labour market adjustments to technology shifts	Stresses the need for an educated and versatile workforce able to move between sectors and roles

Source: Author’s work (2024)

AI affects both jobs that require low levels of expertise and those that require high levels of skill, fundamentally changing the labour market by replacing workers and generating new prospects. Romer's theory (Romer, 1990) emphasises the significance of technical innovation in driving economic growth, indicating that AI can both automate low-skilled professions and stimulate the development of new industries. Schumpeter's theory of creative destruction (Schumpeter, 2013) demonstrates how AI obsoletes certain occupations while concurrently creating new opportunities in various industries, hence requiring a range of distinct proficiencies. Solow's model (Solow, 1957) emphasises the impact of technology on productivity, suggesting that there is a possibility of job creation even if low-skilled positions decrease. Becker's focus on human capital highlights the need for retraining and education to reduce the impact of AI on professions that require low skills (Becker, 2009). On the other hand, high-skilled positions are expected to benefit from AI since it will lead to the development of opportunities in innovative and technologically sophisticated roles. Romer (Romer, 1990) proposes that the innovation of AI would stimulate employment in high-tech industries, while Schumpeter predicts (Schumpeter, 2013) a dynamic labour market characterised by both job destruction and creation. Solow observes (Solow, 1957) that the impact of AI on employment creation would differ across sectors, notwithstanding the potential for productivity enhancements. Becker asserts that there is an increasing requirement for highly qualified workers due to the necessity of adjusting to technological progress (Becker, 2009). Government policies have a crucial role in influencing how the labour market adjusts to AI. It is necessary to develop strategies that promote innovation, effectively manage transitions, and cultivate human capabilities to meet the changing demands of the workplace. The integration of AI poses problems and opportunities for employment, necessitating ongoing learning and adaptability in a rapidly evolving economic environment.

Regarding the RQ1 presented, we can conclude that AI has a significant impact on job dynamics in various sectors. Research has shown that in the field of manufacturing, the implementation of AI and automation technologies often results in the replacement of jobs, especially those that involve routine and manual tasks. On the other hand, in industries like information technology and financial services, AI has sparked the emergence of new job roles that require highly developed technical and analytical abilities. This division in job impacts emphasises the role of AI as more than just a replacement for human labour. It is a transformative force that redefines job roles and the skills they demand. Research results indicate that the impact of AI varies across different geographical areas, indicating that the integration and adoption rates differ from region to region. The local economic structures and policies further influence these variations in place.

Regarding RQ2, we can conclude that with the widespread incorporation of AI into various economic activities, there arises a profound need to reassess and potentially modify conventional economic theories pertaining to growth, productivity, and human capital. For example, the Solow Growth model (Solow, 1957), which typically attributes productivity enhancements to technological advancements, may not fully capture the rapid and transformative impact of AI technologies. The potential of AI to independently enhance and innovate has the power to generate productivity gains that go beyond small steps and instead make significant leaps. The Theory of endogenous growth, as proposed by Romer (Romer, 1990), highlights the significance of knowledge and innovation in fuelling economic growth. AI enhances these aspects by speeding up the pace of innovation and the implementation of knowledge across various industries. This has the potential to result in long-lasting and self-reinforcing growth patterns that were not previously considered in conventional models.

Discussion

A study was conducted to investigate the complex relationship between AI and changes in the labour market. Focus of this paper was on understanding how AI impacts job displacement and creation at different skill levels and the implications this has on economic theories. Detailed insights were gathered from the theories of prominent authors. These insights enrich the discussion on how AI influences current and future labour markets. This research suggests that AI has both positive and negative impacts on the job market. Artificial intelligence, in line with Romer's theory (Romer, 1990), plays a key role in driving substantial economic growth and enhancing productivity by fostering innovation. Following Schumpeter's idea of creative destruction (Schumpeter, 2013), this expansion leads to employment displacement in areas open to automation but also stimulates new job opportunities in developing businesses. Solow's growth model indicates that AI has differing effects on various industries, ultimately leading to beneficial impacts on economic efficiency and output (Solow, 1957). Becker's Human capital theory (Becker, 2009) emphasises the growing significance of education and skill enhancement in preparing the workforce for an economy influenced by AI. The comparison of these views highlights AI's ability to significantly change the labour market significantly, emphasising the importance of being adaptable and always learning. The shift towards a more AI-integrated economy requires a workforce with advanced skills and the ability to adapt to new job categories. One of the most debated topics in this realm is the potential for a “jobless future” (Nübler, 2016), where AI and automation lead to a significant reduction in the demand for human labour. This debate is underpinned by the dichotomy between the optimistic view of technology as a creator of new jobs and the pessimistic view that sees technology as a replacement for human labour. A study by Frey and Osborne (2017) provides an analysis of the susceptibility of jobs to computerisation, indicating that a significant percentage of jobs could be at risk due to AI and automation. However, this potential risk does not uniformly translate into actual job losses, as the study also notes the creation of new job types and the evolution of existing ones. The concern of a jobless future hinges on the balance between the jobs eliminated by AI and those created by it. Meanwhile, low-skill jobs, particularly those involving personal interaction, care services, or complex manual tasks, have largely remained resistant to automation, preserving their demand in the job market. A study by Goos, Manning, and Salomons (2014) provides empirical evidence of this phenomenon, analysing job polarisation across Europe and the United States. Their research indicates a significant shift in employment from middle-skill occupations to both high-skill and low-skill jobs, emphasising the role of technological advancements in driving this change. This evidence suggests that AI and automation are key drivers of labour market polarisation, with significant implications for the workforce and society.

This study offers useful insights into how AI affects labour market dynamics based on recognised economic theories, but it does have limits. The fast progression of AI technology and its widespread use in various industries make it difficult to predict future labour market trends. An example is the incorporation of AI in production, frequently referred to as Industry 4.0, which is altering the manufacturing landscape and labour market dynamics (Schwab, 2017). This analysis is limited by the availability and extent of empirical data, which may not completely represent the subtle effects of AI on different job categories and industries. Moreover, the theoretical frameworks used may not consider all socio-economic aspects affecting labour market dynamics, including global economic developments, regulatory modifications and cultural changes related to work and technology. This research highlights the intricate relationship between AI, economic **expansion,** and labour market trends. Significant variations were identified in the digital preparedness and utilisation of specific cutting-edge digital tools across EU member states (Hunady et al., 2022). The subsequent three primary priorities mentioned in the paper with importance in facilitating digital transformation are: (**a**) the removal of administrative obstacles and the establishment of financial motivations to encourage the digital transformation of businesses; (**b**) the expansion of information and communication technology infrastructure; and (**c**) investments in the acquisition of digital competencies. Countries like Denmark and Sweden lead in embracing digital technologies. In contrast, countries such as Romania and Bulgaria face significant challenges in digital readiness, which underscores the need for targeted digital policies and infrastructure improvements in less advanced areas (Fortis et al., 2022). The results confirm that education, skill development and governmental intervention play a crucial role in addressing the problems of AI and maximi**s**ing its economic advantages. To succeed in the changing work environment influenced by AI, it is crucial to develop a labour market that is resilient, flexible, and welcoming to all. Future stud**ies** should focus on overcoming the stated constraints by includ**ing** more detailed data and investigating the connections between AI, economic policies, and labour market regulations to comprehensively grasp AI's lasting effects on the global economy and workforce.

Skill-biased technological change (SBTC), as propelled by advancements in AI, distinctly highlights the divergence in labour market dynamics between high-skill and low-skill jobs. This phenomenon, significantly influenced by technological progress, disproportionately benefits workers possessing advanced education and specialised training (Weiss, 2008). AI's role in accelerating SBTC has become a pivotal aspect of contemporary labour market analysis, primarily due to AI's proficiency in automating routine tasks and its complementarity with human skills in sectors like healthcare, where it augments the capabilities of medical professionals (Rane, 2023). Moreover, addressing the challenges of SBTC requires a concerted effort across public and private sectors to invest in education and training programs, fostering a culture of continuous learning and adaptation. International cooperation and the sharing of best practices can also play a crucial role in managing the transition to an AI-driven economy more effectively (Aoun, 2017; Frank et al., 2019). Different countries have adopted varied approaches to tackling the challenges posed by SBTC. For instance, the German model of vocational education and training (Brockmann et al., 2008), which combines workplace training with formal education, has been effective in preparing its workforce for technological changes. In conclusion, this exploration of SBTC in the context of AI underscores the complex interplay between technological advancements and labour market dynamics. While AI presents significant opportunities for economic growth and job creation, it also poses challenges that necessitate proactive responses to ensure an inclusive and equitable adaptation to the evolving labour landscape. By integrating internal and external influence factors, some frameworks support management in selecting strategic change options that align with the organisation's operational context and industry ecosystem, paving the way for transformational progress in uncertain environments (Tomičić-Pupek et al., 2023).

Conclusion

This study examines the influence of artificial intelligence on labour market dynamics by analysing key economic theories such as Romer's Endogenous growth theory (Romer, 1990), Schumpeter's Creative destruction (Schumpeter, 2013), Solow's Growth model (Solow, 1957), and Becker's Human capital theory (Becker, 2009) in combination with 105 papers analysed in the literature review section. The results of this study demonstrate that AI has a substantial impact on both economic growth and productivity, aligning with Romer's (Romer, 1990) emphasis on the importance of innovation. The validity of Schumpeter's thesis (Schumpeter, 2013) is supported by the finding that AI leads to job displacement while also generating new opportunities, thus exemplifying the dualistic nature of creative destruction. Solow's model emphasises the diverse effects on different sectors (Solow, 1957), indicating overall positive implications on productivity and economic output. In contrast, Becker's emphasis on education and skill development aligns with the requirement for a workforce that is more educated and adaptive in an economy integrated with AI (Becker, 2009). This study enhances the current research by offering a detailed grasp of how AI is changing labour markets. Prior research has frequently emphasised the transformative capacity of artificial intelligence but has not fully incorporated established economic ideas. This research enhances the academic discussion on the relationship between technological advancements and economic and labour dynamics by comparing these findings with existing theories. It provides a more comprehensive understanding of the various effects of AI, taking into account the rapid development of digital technologies that previous models did not fully incorporate. This research highlights the need for targeted policy actions and educational changes to effectively utilise the potential of AI while minimising its negative impacts. As economies increasingly integrate AI into many sectors, there is an escalating demand for policies that promote ongoing learning, skill enhancement and adaptability within the workforce. This strategy will not only provide individuals with the necessary skills and knowledge to adapt to the changes brought about by AI, but also empower them to prosper in a digitally-driven economic environment. The incorporation of artificial intelligence presents notable difficulties, but it also provides considerable prospects for improving economic stability and expansion through informed strategic planning. Nevertheless, this study has its drawbacks. The swift advancement of AI technologies poses a difficulty in forecasting the long-term effects on the labour market, revealing a deficiency in current economic models that may not sufficiently capture the rapidly changing dynamics of the workforce influenced by technology. Moreover, the access to and analysis of factual information is still restricted. Subsequent investigations should overcome these constraints by utilising increasingly complex and dynamic data sources while prioritising the empirical verification of theoretical forecasts. Continuing research is crucial to ensure that the advantages of AI are dispersed fairly and extensively.

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