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AI and Automation in the Labor Market: Literature Review on Implications for Employment, Skills, and Inclusive Growth*

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Abstract

Labour markets in medium-developed economies are changing under the influence of automation and the digitalisation of production and services. These changes are widely discussed in relation to highly developed economies, but there is still less comparative research on transition and emerging economies. This paper analyses how automation affects employment structures and skill requirements in Poland and Türkiye. The two countries face similar technological pressures, although they differ in their institutional settings, education systems and labour market conditions.The study is based on a comparative review of the literature and secondary data from the World Economic Forum, the OECD, the ILO and national research institutions. The analysis shows that automation mainly affects routine and medium-skill jobs, while increasing the demand for digital competencies, analytical thinking and interpersonal skills. Poland appears to be more advanced in the shift towards high-skill employment, although skill gaps remain visible. Türkiye, in turn, faces more basic challenges related to digital and foundational literacy. In both countries, one of the main problems is the mismatch between the speed of technological adoption and the readiness of workers to adapt to these changes. The paper argues that the long-term effects of automation will depend not only on technology itself, but also on lifelong learning, labour market policy and investment in human capital.

Keywords: artificial intelligence; automation; labour market; employment structure; skills transformation; technological change; Poland; Türkiye

Introduction

The labour market of the 21st century is undergoing profound transformations driven by rapid technological progress, particularly in the fields of artificial intelligence and automation. Advances in digital technologies, machine learning, and automation systems are increasingly reshaping production processes, organizational structures, and the nature of work itself. As a result, the contemporary economy is characterized by a growing reliance on advanced technologies, which significantly affects both employment patterns and skill requirements across sectors. Technological change has historically been a key driver of economic development and productivity growth; however, the current wave of automation differs from previous ones in its scope, speed, and potential to affect not only routine manual tasks but also cognitive and knowledge-based activities. These developments raise important questions regarding the future of employment, the risk of job displacement, and the changing relationship between human labour and intelligent machines. In this context, the debate on whether artificial intelligence substitutes or complements human work has become central to labour market analysis.

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Moreover, the diffusion of AI technologies intensifies the demand for new competencies while simultaneously reducing the relevance of certain traditional skills. This process contributes to the emergence of skill gaps, labour market polarization, and growing inequalities between high and low-skilled workers. Consequently, education systems, universities, and lifelong learning frameworks face increasing pressure to adapt to the evolving requirements of the AI-driven economy. The ability of workers to reskill and upskill has become a crucial factor determining their employability and long-term participation in the labour market.

The presented article aims to analyse the impact of artificial intelligence and automation on employment and skill structures from a theoretical perspective. Attention is paid to key economic theories explaining technology-driven labour market shifts, as well as to the differentiated effects of automation across sectors and occupations. Additionally, the article discusses the economic and social consequences of these processes, with a comparative focus on Poland and Türkiye as economies experiencing distinct but converging challenges related to technological transformation. The main thesis of the article is that while artificial intelligence poses significant risks to certain categories of employment, its overall impact on the labor market depends largely on institutional responses, education systems, and public policies supporting workforce adaptation. Despite the growing body of literature on artificial intelligence and labour market transformations, there is still a limited number of comparative studies focusing on medium-developed economies with distinct institutional, educational, and labour market structures. Comparative analyses of Poland and Türkiye remain underexplored, despite both countries facing similar technological pressures while differing significantly in their economic composition and human capital development.

The selection of Poland and Türkiye as case studies is justified by their status as transition and emerging economies characterized by medium levels of development, relatively diversified economic structures, and evolving labour market institutions. Poland, as a member of the European Union, benefits from access to EU digital policies and funding mechanisms, while Türkiye follows a distinct development path shaped by different institutional and educational frameworks. This makes the comparison particularly relevant for understanding how similar technological forces interact with different structural conditions. This study aims to address the following research questions:

1. How does artificial intelligence affect employment structures in Poland and Türkiye?
2. What differences can be observed in skill transformation and labour market adaptation between the two countries?
3. What are the key economic and social consequences of automation in both contexts?

The article is structured as follows. The first section presents the theoretical framework and reviews the relevant literature on technological change and labour markets. The second section outlines the research methodology and data sources. The following sections analyze the impact of artificial intelligence on employment structures, skills transformation, economic outcomes, and social consequences. The final sections provide a comparative synthesis, policy recommendations, and concluding remarks.

Theoretical Framework: AI, Automation, and Labor Market Transformations

The theoretical foundations of research on artificial intelligence, automation, and labor market transformations are rooted in broader economic theories of technological change and its impact on employment. Early classical economists already recognized that technological progress could displace labor in the short run while increasing productivity and employment in the long run through compensation mechanisms (Ricardo, 1821; Marx, 1867). Subsequent historical analyses distinguish several waves of technological change, including mechanization during the Industrial Revolution, electrification and mass production in the early 20th century, computerization in the late 20th century, and the current wave driven by digitalization, artificial intelligence, and data-intensive technologies (Perez, 2002; Brynjolfsson & McAfee, 2014). Within contemporary labor economics, a dominant analytical framework is the task-based approach, which conceptualizes jobs as bundles of tasks that may be differentially affected by automation depending on their routine or non-routine character (Autor et al., 2003). This perspective underpins the theory of routine-biased technological change, explaining employment polarization observed in many advanced economies (Autor, 2015). Complementing this view, more recent theoretical contributions emphasize the distinction between labor-substituting and labor-augmenting technologies, arguing that the employment effects of AI depend on whether intelligent systems replace human tasks or enhance worker productivity (Acemoglu & Restrepo, 2020). Together, these theoretical perspectives provide a comprehensive framework for understanding how artificial intelligence reshapes labor demand, skill structures, and employment dynamics in modern economies.

Additional theoretical perspectives highlight how the effects of AI depend on institutional complements and the direction of innovation. The Skill-Biased Technological Change (SBTC) framework argues that technological progress disproportionately increases demand for high-skilled labor, reinforcing wage inequality unless education systems expand sufficiently fast (Goldin & Katz, 2008). Directed Technical Change theory further shows that innovation tends to favor factors that are either scarce (price effect) or abundant (market-size effect), depending on the elasticity of substitution between capital and labor (Acemoglu, 2002). Finally, research on AI-driven inequality indicates that without adequate redistribution and training systems, worker-replacing technologies may increase both income dispersion and transitional unemployment (Korinek & Stiglitz, 2017). Together, these perspectives clarify why AI adoption produces heterogeneous outcomes across countries and sectors.

Methodology

The study is based on a comparative analytical approach combined with a literature review and secondary data analysis. It draws on established theories of technological change and labour economics, grounded in the relevant academic literature. The reports and data used in the analysis come from reputable international institutions, including the World Economic Forum, the International Labour Organization, and the OECD, as well as national sources such as publications by the Polish Economic Institute. An important complementary source is the EY Work Reimagined Survey (2025), which provides insights into organisational practices and workforce adaptation.

The selection of Poland and Türkiye for comparative analysis is not accidental. Both countries can be considered representative examples of medium-developed economies undergoing technological transformation under different institutional and socio-economic conditions. The analysis focuses on the qualitative interpretation of quantitative indicators, including employment structure, skill distribution, and measures of exposure to automation, with particular attention paid to sectoral and occupational differences.

The study has several limitations. First, it relies exclusively on secondary data, which may differ in methodology and may not always be fully comparable across sources. Second, the analysis is conducted at a highly aggregated level and does not capture firm-level or individual-level variation. Despite these limitations, the paper provides a current and theoretically grounded perspective on labour market transformations related to the development and implementation of AI in Poland and Türkiye.

Impact of AI on Employment Structures

The assessment of automation risk is often based on task characteristics and the susceptibility of occupations to technological substitution. According to Frey and Osborne (2017), approximately 47% of jobs in advanced economies are at high risk of automation, particularly those involving routine and predictable tasks. However, subsequent task-level analyses have substantially revised this estimate downward, finding that only around 9% of jobs in OECD countries face high automation risk when within-occupation heterogeneity is accounted for (Arntz et al., 2016). Similarly, OECD classifications distinguish between occupations with high, medium, and low exposure to automation, emphasizing the importance of task content rather than entire job categories (OECD, 2019).

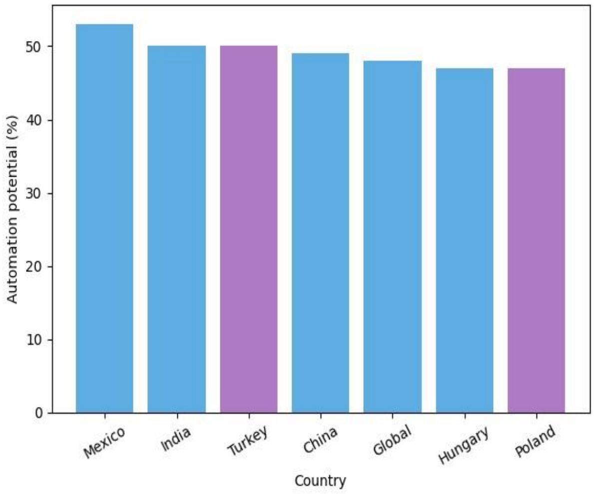

Figure 1. Automation potential across selected countries.Source: O*NET; McKinsey Global Institute Automation Model (May 2019).

In this context, occupations involving routine cognitive and manual tasks are more likely to be automated, while jobs requiring complex problem-solving, creativity, and interpersonal interaction remain relatively resilient. This framework is particularly relevant for analyzing differences between Poland and Türkiye, where sectoral structures and occupational distributions vary significantly. Rapid advances in AI and automation technologies have the potential to significantly affect labor markets and employment structures. While AI and automation increase productivity gains and new task generation, they can also replace labor demand in such routine-intensive occupations. According to Figure 1, the results show that Türkiye and Poland have relatively high automation potential amid a high concentration of manufacturing and agriculture, which have a high percentage of predictable work activities.

As a result of automation, the main expectation is that demand for some occupations is rising substantially; others are being displaced or transformed. Global evidence suggests that task substitution will continue to affect routine clerical, administrative and middle-skill occupations, while growth is expected in analytical, creative, and interpersonal roles (Frey & Osborne, 2017; Autor, 2015). In Poland, exposure is particularly high among office workers and women, who are overrepresented in administrative and clerical occupations (Korgul et al., 2024; Troszyński et al., 2025). Türkiye's employment structure remains more dependent on medium-skill and routine tasks, which increases vulnerability to automation but also highlights potential productivity gains if complemented with adequate training (OECD, 2023b). Consequently, both countries face significant but distinct structural pressures: Poland towards upgrading services and knowledge-intensive sectors, Türkiye towards raising foundational and digital skills in the workforce. These unbalanced labor demands can be the cause of job polarization and disproportionate wage gains. Growth of employment structured around relatively high-skill, high-wage, and low-skill, low-wage jobs at the expense of "middle-skill" jobs.

Consistent with this analysis, Figure 2 illustrates Poland's employment structure, which shows a clear shift toward high-skill occupations, with their share rising from about 41% in 2020 to 45% in 2024, alongside a decline in medium and low-skill employment. In contrast, Türkiye's skill composition remains relatively stable, with a modest increase in high-skill employment while medium-skill occupations continue to dominate.

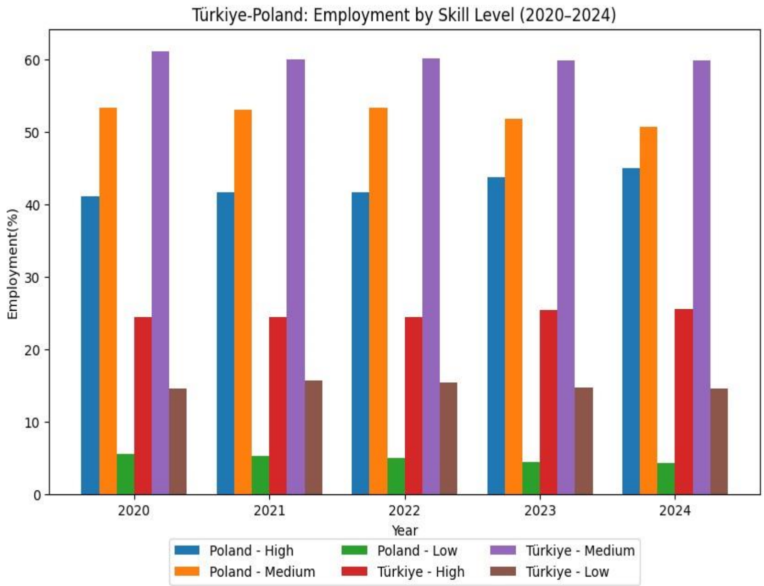

Figure 2: Employment by Skill Level in Türkiye and Poland (2020–2024).Source: International Labor Organization (ILO), ILOSTAT database

Although AI and automation displace or transform some existing occupations, they also create new ones and boost productivity. According to the World Economic Forum (2025), over the next five years, 170 million jobs are expected to be created and 92 million displaced, representing a structural labor market churn of 22% of the 1.2 billion formal jobs in the dataset. This implies a net increase of 78 million jobs, corresponding to a 7% rise in total employment.

According to real users' data of Anthropic AI *(Appel et al., 2026)*, Poland is the 32nd and Türkiye the 72nd country with the most use of the Anthropic AI. The usage purpose of it 12% coursework, 40% personal, 48% work in Poland and 17% coursework, 40% personal, 43% work in Türkiye. The data also suggests that collaboration with AI systems can significantly reduce task completion time.

Skills Transformation and Educational Challenges

AI and automation are reshaping the demand for skills across labor markets. While routine cognitive and manual tasks are increasingly automated, demand is rising for analytical, digital, and socio-cognitive skills. Workers are expected to complement intelligent systems rather than compete with them.

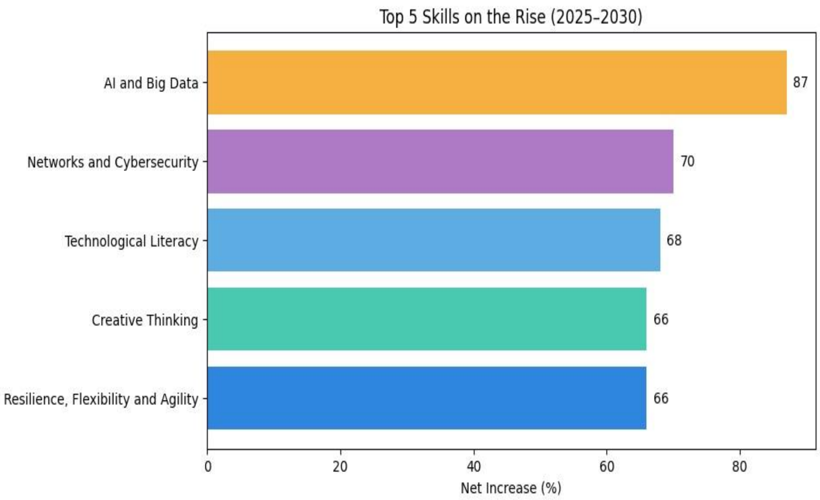

Figure 3: Skills are ranked based on net increase, defined as the difference between the share of employers reporting increasing use and those reporting decreasing use. Source: World Economic Forum – Future of Jobs Report.

Evidence from the Future of Jobs Report published by the World Economic Forum (2025) indicates the growing importance of technological and cognitive competencies in the coming years. As shown in Figure 3, the fastest-growing skills between 2025 and 2030 include AI and Big Data, Networks and Cybersecurity, and Technological Literacy. At the same time, cognitive abilities such as Creative Thinking and Resilience, Flexibility and Agility are also expected to increase significantly, highlighting the importance of combining technical knowledge with human-centered capabilities.

These changes pose important challenges for education systems and workforce development policies. Universities and training institutions need to adapt curricula to better reflect the demands of the AI-driven economy by strengthening digital literacy, data-related competencies, and problem-solving skills. In the case of Poland and Türkiye, improving access to digital education and lifelong learning opportunities will be essential to reduce skill mismatches and support workforce adaptation. Consequently, policies promoting reskilling and upskilling will play a crucial role in enabling workers to transition toward occupations that complement emerging AI technologies. In the context of Poland and Türkiye, the skills gap reflects both technological and structural challenges. In Poland, despite progress in digitalization, a significant share of the workforce still lacks advanced digital competencies, and the level of ICT specialization remains below the European Union average (European Commission, 2024). At the same time, OECD data indicate that Polish adults perform below the OECD average in key cognitive skills, including literacy and problem-solving (OECD, 2023a).

In Türkiye, the skills gap is more pronounced and relates not only to digital competencies but also to foundational skills. According to OECD data, a considerable proportion of adults lack basic proficiency in technology-rich environments, which limits their ability to effectively adopt and use AI-related tools (OECD, 2023b). These findings suggest that the skills gap is not only a technological issue but also an institutional and structural one, requiring coordinated efforts across education systems, labor market policies, and organizational practices. Recent findings show that AI adoption amplifies the demand for advanced digital literacy, data reasoning, creative problem-solving, and resilience, reflecting the shift toward human-machine complementarity (World Economic Forum, 2025). However, organizations often underestimate the importance of training: while almost 90% of employees report using AI tools, only about 12% receive adequate support, contributing to rising workload pressure and skill anxiety (EY, 2025). These “training gaps” reduce up to 40% of potential productivity gains, demonstrating that the economic value of AI is contingent not on access to technology but on the presence of strong learning systems, governance frameworks, and job-redesign practices (EY, 2025).

Economic Effects of Automation

The economic effects of automation and artificial intelligence are multidimensional and unevenly distributed across sectors and labour market groups. In literature, AI is most often associated with productivity gains, cost reduction, and the acceleration of knowledge-intensive processes (Brynjolfsson & McAfee, 2014). However, these benefits are not automatic. As emphasized by Acemoglu and Restrepo (2020), the overall impact of AI depends on whether technological change is labor-augmenting or labor-replacing. According to the World Economic Forum (2025), technological transformation will simultaneously generate and displace jobs, leading to a net increase in employment but also a structural reconfiguration of labor demand. From the perspective of Poland and Türkiye, productivity gains from AI are strongly linked to sectoral composition and workforce characteristics. In Poland, AI exposure is concentrated in occupations requiring higher education, particularly in administrative and analytical roles. According to NASK and ILO research, approximately 30.3% of jobs in Poland are exposed to generative AI, with office workers representing the most affected group (Troszyński et al., 2025).

In Türkiye, the potential productivity benefits of AI are more constrained by lower average levels of digital and cognitive skills. OECD data indicate that adults in Türkiye perform below the OECD average in literacy, numeracy, and problem-solving in technology-rich environments (OECD, 2023b). This suggests that AI-driven productivity gains may be concentrated in more advanced firms and regions. A crucial dimension of economic impact is organizational readiness. According to the EY Work Reimagined Survey, although 88% of employees report using AI tools, only 12% have received sufficient training, which limits the realization of productivity gains (EY, 2025). This finding highlights that technology adoption without adequate investment in human capital significantly reduces potential efficiency improvements.

Automation also affects wage structures and the broader distribution of economic opportunities. The literature on skill-biased and routine-biased technological change indicates that workers performing tasks complementary to AI benefit from wage growth, while those in routine occupations face wage pressure (Autor, 2015). These dynamics are compounded by growing skills gaps: evidence from successive editions of the WEF Future of Jobs Reports indicates that the share of firms identifying competency shortages as the primary barrier to technological transformation rose from 55% in 2020 to 63% in 2025, reflecting the widening divide between technology adoption and workforce preparedness (Maszczykowska, 2024). This suggests that the economic impact of artificial intelligence is not determined solely by technological adoption, but by the ability of firms and institutions to effectively integrate human capital into digital transformation processes. International comparisons of robot density illustrate the uneven potential for productivity gains. The EU average reached 219 robots per 10,000 manufacturing workers in 2023, while Poland's robot density stood at approximately 81 units per 10,000 manufacturing employees in 2024, well below the EU benchmark, indicating significant room for automation-driven productivity growth (IFR, 2024). Such gaps suggest that the economic returns from AI and automation will depend not only on digital readiness but also on the scale and sectoral targeting of capital investment. Without complementary improvements in worker skills and managerial practices, automation may raise efficiency in isolated pockets rather than across the wider economy (Acemoglu & Restrepo, 2020).

Social Consequences and Inequality

Automation and artificial intelligence have significant social consequences, particularly in relation to labor market polarization and inequality. According to the task-based approach, jobs consisting of routine tasks are more susceptible to automation, while non-routine cognitive and interpersonal jobs are more resilient (Autor et al., 2003). This leads to labour market polarization, characterized by the growth of high-skill and low-skill employment at the expense of middle-skill occupations (Autor, 2015). In Poland, the social impact of AI is already visible. According to the Polish Economic Institute, women are more frequently employed in occupations highly exposed to AI, and workers with tertiary education dominate in these groups (Korgul et al., 2024). Similarly, research by NASK and ILO indicates that women are overrepresented in AI-exposed occupations across all age groups, particularly in administrative roles (Troszyński et al., 2025).

These patterns suggest that AI may reinforce existing inequalities if not accompanied by targeted policy interventions. The distributional effects of automation are therefore closely linked to access to education, digital skills, and labour market opportunities.

Social risks also include work intensification and growing uncertainty. According to EY (2025), 64% of employees report increased workload pressure, while 37% express concerns that AI may weaken their professional expertise. Additionally, the widespread use of so-called “shadow AI” indicates a gap between technological adoption and organizational governance. AI-driven task reconfiguration intensifies existing labor-market inequalities, particularly where access to training and digital tools is uneven. Both survey and firm-level evidence indicate rising concerns around skill erosion, increased pace of work, and stress linked to constant performance monitoring (EY, 2025). These risks underline the need for organizational governance frameworks that regulate AI use in workplaces, ensure transparency, and protect workers from excessive workload amplification or algorithmic bias (Korinek & Stiglitz, 2017). In countries with existing skill divides-such as Poland’s literacy/numeracy gap or Türkiye’s digital-skills gap-the social consequences of AI may deepen polarization if institutions fail to provide accessible and continuous learning opportunities (OECD, 2023a, 2023b).

In Türkiye, inequality related to automation is strongly influenced by disparities in digital competencies. OECD data show that a significant proportion of adults lack basic digital skills, and younger cohorts perform significantly better than older ones (OECD, 2023b). This creates a risk of generational and educational inequality in access to AI-related opportunities. Therefore, the key social challenge is not only job displacement, but also unequal capacity to adapt to technological change. Workers with access to training, education, and digital tools are more likely to benefit from AI, while others may experience exclusion. Therefore, artificial intelligence should be understood not only as a technological driver, but also as a factor reshaping social structures, labor market dynamics, and the distribution of economic opportunities.

Comparative Perspective: Synthesis

A comparative analysis of Poland and Türkiye reveals both similarities and important structural differences in their readiness for automation. In both countries, AI is expected to transform labour markets through task reconfiguration rather than simple job elimination. This aligns with global findings indicating that automation leads primarily to job transformation and skill shifts (World Economic Forum, 2025). Poland appears relatively better positioned to benefit from AI in service-oriented and knowledge-intensive sectors. The country has experienced growth in digital skills and ICT employment, although it still remains below the EU average (European Commission, 2024). At the same time, OECD data indicate that Polish adults still perform below the OECD average in key competencies, which may limit the speed of adaptation (OECD, 2023a). Türkiye, in contrast, faces more fundamental challenges related to human capital. Lower levels of digital literacy and broader disparities in education may result in a more uneven adoption of AI technologies (OECD, 2023b). As a result, technological transformation may be concentrated in selected sectors and regions.

Despite these differences, both countries face a common challenge: the gap between technological adoption and workforce preparedness. Evidence suggests that without adequate training systems and institutional support, the potential benefits of AI will not be fully realized (EY, 2025). This comparison highlights that technological readiness is path-dependent and shaped by historical, institutional, and educational trajectories. Scenario analysis to 2030 indicates three divergent pathways. An optimistic "augmentation scenario" assumes effective lifelong-learning systems, rapid diffusion of digital and cognitive skill-building, and strong organizational governance, enabling AI to boost productivity without widening inequalities (World Economic Forum, 2025). A pessimistic "displacement scenario" emerges if training and policy reforms lag behind technological adoption, leading to skill mismatches, wage polarization, and uneven regional development (Korinek & Stiglitz, 2017). The most likely outcome for both Poland and Türkiye is a hybrid trajectory in which gains materialize in digitally advanced sectors, while structural barriers persist in regions and industries with weaker human-capital foundations (OECD, 2023a, 2023b). For Poland, the augmentation scenario is within reach in knowledge-intensive service sectors - business services, IT, and public administration - where high-skill workers already interact with AI tools and where EU-funded upskilling programs provide a structural foundation. The displacement scenario is more likely in manufacturing and agriculture, where medium-skill workers face automation pressure without adequate reskilling infrastructure. For Türkiye, the hybrid trajectory implies a sharper geographic divide: metropolitan areas with stronger educational institutions may achieve productivity gains comparable to EU averages, while rural and less-educated populations risk being bypassed by the AI transition entirely. In both countries, the realization of the optimistic scenario depends critically on three conditions: the speed and quality of curriculum reform in secondary and tertiary education, the willingness of employers to co-invest in worker training, and the effectiveness of government institutions in translating digital policy frameworks into on-the-ground program delivery.

Discussion and Recommendations

The findings of this study confirm that the impact of artificial intelligence on labour markets depends primarily on institutional and policy responses rather than on technology itself.

As highlighted in the literature, AI may either substitute or complement human labour, and the balance between these effects is shaped by education systems, labour market policies, and business practices (Acemoglu & Restrepo, 2020). First, public policy should prioritize lifelong learning and reskilling systems. According to EY (2025), employees who receive extensive AI training achieve significantly higher productivity gains than those with minimal training. This indicates the importance of investing not only in access to training, but also in its quality and relevance. Second, labour market policies should address the unequal distribution of automation risks. In Poland, women and office workers are particularly exposed to AI-related changes, which requires targeted support programs (Korgul et al., 2024; Troszyński et al., 2025). In Türkiye, policy efforts should focus on improving basic digital competencies and reducing structural inequalities in access to education (OECD, 2023b). Third, businesses should treat AI as a strategic organizational transformation rather than a purely technological investment. Evidence shows that firms often fail to fully utilize AI due to insufficient integration with human capital strategies (EY, 2025). Fourth, educational institutions should adapt curricula to the requirements of the AI-driven economy. According to the World Economic Forum (2025), the most important future skills include analytical thinking, technological literacy, and resilience. This highlights the need for interdisciplinary education combining technical and cognitive competencies. Finally, future research should focus on task-level analysis, longitudinal data, and comparative studies of emerging economies. There is still a lack of detailed evidence on how AI affects wages, job quality, and mobility over time.

The findings of this study contribute to the broader debate on the future of work by demonstrating that technological change does not operate in isolation, but interacts with institutional, economic, and social structures. Policies should therefore prioritize phased and scalable skill-development systems: foundational literacy and numeracy upgrades (especially critical in Poland's adult population), digital-skills bootcamps for low-skill and medium-skill workers, and micro-credential pathways in AI, data analysis, and cybersecurity (OECD, 2023a, 2023b; World Economic Forum, 2025). Firms need structured AI governance-clear usage rules, risk assessments, data-handling protocols, and transparent decision-making-and job-redesign processes that decompose roles into automatable and augmentable tasks (EY, 2025). Governments should incentivize employer training through tax credits, subsidized upskilling, and regional competence centers, particularly in areas where workforce digital readiness remains low (OECD, 2023a, 2023b).

Conclusions

This study demonstrates that artificial intelligence and automation are transforming labour markets in complex and multifaceted ways. Rather than leading to universal job loss, AI contributes to the restructuring of employment, skill requirements, and economic relations (Acemoglu & Restrepo, 2020). The comparative analysis of Poland and Türkiye shows that both countries face similar global pressures but differ in their capacity to adapt. Poland’s challenge lies in managing structural transformation and mitigating inequality, while Türkiye must focus on strengthening its human capital base and digital competencies. The results suggest that the future of work will depend on institutional choices. Without adequate policy responses, AI may increase labour market polarization and inequality. However, with effective investment in education, reskilling, and inclusive labour market policies, AI can become a complementary force supporting economic growth and social development (World Economic Forum, 2025; EY, 2025).

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