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ARTIFICIAL INTELLIGENCE, WORK FRAGMENTATION AND INEQUALITY IN AN UNCERTAIN ECONOMY

Victor FELEA and Carmina-Ruxandra ION

National University of Political Studies and Public Administration (SNSPA), Bucharest, Romania
victor.felea.22@drd.snspa.ro; carmina.ion.22@drd.snspa.ro;

Abstract: *The adoption of artificial intelligence is accelerating within a global economic environment characterized by persistent inflation, tighter financial conditions, and geopolitical uncertainty. Under these constraints, firms increasingly deploy AI to enhance efficiency, control costs, and reorganise production processes. This study examines patterns of AI adoption across firms and analyses their implications for job stability and career trajectories. Evidence suggests that AI is primarily implemented at the task level, reshaping work organization, intensifying performance expectations, and modifying pathways of upward mobility. At the same time, integration of AI technologies remains uneven, favouring larger firms and workers with stronger complementary skills, while exposing routine and lower skilled roles to greater risks of stagnation and displacement. These dynamics are further explored through the case of Romania, a semi-peripheral economy embedded in European production networks and characterised by structural inequalities, labour shortages, and limited digital skills. In this context, AI adoption interacts with pre-existing constraints, including regional disparities, demographic pressures, and uneven access to education and technological infrastructure. Rather than generating uniform productivity gains, AI is likely to reinforce existing divisions between firms and workers, widening gaps in opportunities and outcomes. The findings suggest that AI operates not only as a driver of efficiency, but also as a mechanism that reshapes labour market inequalities under conditions of economic uncertainty.*

Keywords: *Artificial Intelligence; Labour Market Transformation; Job Stability; Economic Uncertainty; Inequality.*

JEL Classification: *O00; O38; J08*

1. Introduction

Recent global economic developments point to a period marked by overlapping pressures rather than a single dominant trend. The International Monetary Fund notes that inflation has proven more persistent than initially expected, while overall growth has slowed compared to pre-pandemic levels (IMF,2025). Geopolitical tensions have also played a role. The World Bank highlights rising uncertainty linked to conflict and trade disruptions (World Bank, 2025), a pattern that can be seen in the continued effects of the war in Ukraine and reinforced by ongoing conflicts in the Middle East. In parallel, tighter financial conditions and higher borrowing costs have constrained investment, particularly in advanced economies (OECD, 2024).

The growing use of artificial intelligence in business can be understood within the broader wave of digital innovation described by Brynjolfsson and McAfee (2014), who highlight how advances in computing power, data availability, and digital technologies are reshaping how firms operate and compete. Artificial Intelligence is now a widely adopted organizational tool, increasingly shaping business strategy, labour organization, and firm-level restructuring. This growing importance of AI in firm behaviour raises important questions about how its adoption varies across firms and how these differences translate into broader economic and labour market outcomes. Persistent inflationary pressures and tighter financial conditions have limited firms' operational flexibility, leading them to treat labour as a flexible cost, while making technological substitution more economically attractive.
Even as AI uptake continues to expand, its broader implications for job stability and career trajectories remain uncertain. AI may reshape career pathways by disrupting the job transitions through which workers typically access higher-paying roles (Brookings Institution, 2026) and the effects of AI adoption are not evenly distributed. Larger firms and workers with higher levels of skills are generally better positioned to benefit, while those in more routine or lower-skilled roles face a higher risk of stagnation or displacement. In this context, the article addresses two main questions: what is the current level and pattern of the integration of AI technologies across firms, and how does AI affect job stability and career paths under conditions of global economic uncertainty? The central argument is that AI does not affect all workers in the same way. Instead, it tends to reinforce existing inequalities while creating new, uneven opportunities across firms and skill groups.

2. Literature review

2.1 Informational technology and global changes in labour structure

The evolution of technological development has historically been associated with changes in labour structure, representing both a form of economic expansion and a source of structural change within societies (Frey and Osborne, 2017). Advances in information technology reshaped economic and labour structures, facilitating the coordination of complex activities at a global scale (Baldwin, 2016). The expansion of internet access and rapid connectivity has enabled new forms of coordination, gradually reorganising labour structures beyond territorial boundaries and supporting the general externalisation of professional activities at a global scale (Crouch, 2018). These advanced technologies have contributed to new forms of governance in work relations under the global division of labour (Huws, 2014). As jobs expanded globally, the global middle class also expanded, while many segments of the workforce in developed countries experienced stagnation (Milanovic, 2016). From this point of view, the new extension of work has functioned primarily as a mechanism for distributing labour costs globally while prioritising upper segments of the organisational structures (Autor, 2015; Piketty, 2017). The reorganisation of labour markets, under conditions of economic competitiveness, has further increased the prevalence of flexible employment arrangements and intensified power imbalances within global organisations (Kalleberg, 2018). Over decades of progression, despite the expanding capabilities of information technologies, the new division of work has enabled higher levels of productivity and profitability while raising concerns over job quality (Streeck, 2016). The new global division of labour initially oriented academic efforts toward the assessment and improvement of job quality. These efforts were reflected in the European Job Quality Index, as well as in other research initiatives using comparable methodological approaches. Early research focused on key dimensions of employment, particularly financial incomes, job security, career opportunities, and autonomy (McGovern et al., 2004; Leschke and Watt, 2008; Block et al., 2018). Over time, increasing global competitiveness and changing employment arrangements redirected academic attention toward the analysis of new forms of work precarity (Kalleberg, 2018). The expansion of non-standard employment allowed employers to lower costs and left workers more exposed to income and employment insecurity. Contemporary research has further expanded the literature on precarity, as the emergence of digital platforms and the gig economy has reinforced new forms of flexible arrangements associated with reduced job stability, limited income security, and restricted career progression (Standing, 2021).

2.2 The emergence of gig economy

If early developments in information technology primarily restructured competences while maintaining, or even increasing, occupational levels, more recent developments have been associated with employment insecurity and pressures on social protection. The literature addresses these preoccupations across different fields of research, such as work standardisation, data control, and flexibility associated with algorithmic platforms (Fernández-Macías et al., 2025). The capabilities of algorithmic performance monitoring, task allocation, and algorithmic evaluation represent a growing field of study in organisational practices, with specific implications for job quality (OECD, 2025).
Digital work platforms represent a different phase in the reorganisation of labour, professional relations, and employment conditions. The gig economy has become a central preoccupation, as digital platforms increasingly mediate and autonomously organise flexible work arrangements outside established labour regulatory frameworks (Vallas & Juliet, 2020). The digital contracting of professional work through non-standard arrangements is generating new vulnerabilities, especially in terms of low levels of legal protection, limited accountability, and uneven task allocation (Bajwa et al., 2018; Woodcock & Graham, 2020). Within the European Union context, social protections continue to apply primarily to standard employment relationships, leaving many self-employed and platform workers outside existing regulatory frameworks. As technological progress accelerates these transformations, concerns occur regarding the capacity of governments to regulate emerging forms of work effectively (Hauben et al., 2020).

2.3 AI adoption and further challenges to labour markets

Contemporary labour markets are undergoing continuous structural reorganisation shaped by the logics of algorithmic platforms, while further advances in artificial intelligence may directly affect occupational structures and professional competencies. The labour market effects of artificial intelligence are better understood through changes in tasks rather than direct job displacement. Firms rarely substitute entire occupations, instead, tend to introduce AI into individual activities such as data processing, customer interaction, or routine administrative work. Recent studies indicate that AI is mainly implemented at the task level, where it enhances efficiency in areas like writing, programming, and information processing

(Brynjolfsson, Li and Raymond, 2023; Noy and Zhang, 2023). When analysing labour market change, it can be argued that new forms of artificial intelligence are unlikely to generate immediate large-scale unemployment (Vallas and Kovalainen, 2019). Instead, current developments point toward a transitional phase in the implementation of algorithmic systems (Jarrahi et al., 2021), in which generative AI is primarily used for task-level activities (Bick, Bladin and Deming, 2024). However, even task-level automation can have significant implications for labour demand. Hampole et al. (2025) show that greater exposure to AI is associated with shifts in demand across tasks, including declines in some activities and increased demand for tasks that complement AI. The primary motivation for AI integration appears to be efficiency improvement rather than direct labour substitution. Firms frequently deploy AI to automate routine labour, enabling employees to manage increased workloads and respond to operational pressures such as staffing shortages and rising demand (Filippucci et al., 2024; Lane and Saint-Martin, 2021). This suggests that AI primarily reorganises tasks rather than replacing entire occupations.

2.4 Inequality and uneven outcomes of AI adoption

The new developments have important implications for competences demand and inequality. AI tends to increase the value of complementary capabilities such as problem-solving, creativity, and digital literacy, while placing greater pressure on routine cognitive tasks. Research shows that AI exposure is uneven across occupations, with many highly exposed roles concentrated in knowledge-intensive work (Eloundou et al., 2024). In addition, evidence from labour market data suggests that demand for AI-related competencies is associated with higher wages in job postings (Alekseeva et al.,2021). As a result, the benefits of AI are unlikely to be distributed evenly. AI adoption is also highly uneven across firms. Empirical evidence shows that AI use is more common among larger firms and those with stronger complementary assets, such as data, capital, and technical expertise (McElheran et al., 2024). This uneven diffusion can widen existing gaps in productivity and performance between firms and indirectly between their workers. In this sense, AI operates not only as a source of efficiency gains but also as a driver of structural inequality within the economy, as automation technologies can generate uneven labour market outcomes (Acemoglu & Restrepo, 2020). Parallel to these developments, firms are increasingly adopting algorithmic management systems to coordinate and monitor labour, using automated tools for task allocation, performance evaluation, and real-time supervision (Lee et al., 2015).

3. Economic challenges and drivers of AI integration

The recent wave of artificial intelligence adoption must be understood within a broader context of overlapping economic shocks, including the COVID-19 pandemic, labour market disruptions, and rapid technological change. AI uptake should not be analysed as an isolated technological trend, but as part of broader structural changes in how firms organise production, use data, and respond to economic uncertainty. The pandemic marked an important moment in this process by accelerating digitalisation across sectors, particularly through the expansion of remote work, online services, and cloud-based systems. At the same time, it made existing inequalities in firms' technological capabilities more visible. These developments contributed to the expansion of firms' digital infrastructure, which supported later the adoption of more advanced technologies such as artificial intelligence (Arroyabe et al., 2024). However, this transition did not occur uniformly. Firms with established digital infrastructures were able to incorporate AI tools more rapidly, whereas less digitalised firms lagged. As documented by the World Bank and the United Nations Conference on Trade and Development (2025), AI adoption remains uneven across firms and countries, reflecting differences in digital infrastructure, data availability, skills, and institutional capacity, which shape firms' ability to adopt and benefit from AI.

The expansion of digital channels during the COVID-19 period marked a shift in how firms organise economic activity. As sales, communication, and coordination increasingly moved online, the volume and strategic importance of digitally generated data grew significantly. Research shows that e-commerce adoption accelerated as in-person transactions became constrained, while firm performance increasingly depended on digital capabilities such as data use and business intelligence (Huy and Phuc, 2023). At the same time, firms with stronger pre-existing digital capabilities were better able to adapt to the shock, contributing to widening differences in performance between more and less digitally prepared firms (Avalos et al., 2024). These developments reinforced existing differences in firms' digital preparedness for adoption.

Simultaneously, tightening labour markets and the emergence of generative AI technologies after 2022 have strengthened incentives for firms to automate and reorganise production processes. The spread of generative AI across firms has been rapid, although its use remains concentrated in specific tasks and often requires complementary organisational and skill-related investments.

The development of generative and related AI technologies has been particularly visible across several key service sectors, where applications have moved from experimentation to operational use. In customer service, evidence from a large-scale study of over 5000 support agents shows that access to a generative AI assistant increased productivity by around 15 per cent on average, with especially strong effects for less experienced workers (Brynjolfsson, Li and Raymond, 2025). For developing economies that specialise in outsourced services, the risk is stated even more. Egana-delSol and Vargas-Faulbaum (2025) surveying AI and labour-market evidence for developing economies, warn that in economies such as the Philippines, extensive call-centre operations and subcontracted roles may be supplanted by chatbots. In the United States, higher regional AI deployment has been associated with larger declines in the employment-to-population ratio, especially in manufacturing, lower-skill services, and non-technical occupations (Huang, 2024). Cross-country evidence from Brazil and the United Kingdom suggests that adjustment differs by education, with college-educated workers more likely to move into high-exposure occupations that are complementary to AI, while less-educated workers face a higher risk of transitioning toward lower-exposure roles and potential income losses (Cazzaniga et al, 2024).

Recent research shows that the development of frontier AI capabilities is highly concentrated in a small number of firms and countries, with advanced economies dominating investment, research, and infrastructure (UNCTAD, 2025). Evidence further indicates that countries with stronger human capital, particularly in STEM fields, and better digital infrastructure tend to perform better in sectors with higher exposure to AI (Bonfiglioli et al., 2025). At the same time, OECD (2025) suggests that AI integration could transform global value chains and place new adoption pressures on firms and national economies. In developing regions, a significant

share of jobs could benefit from AI-driven productivity gains, but limited digital access and infrastructure often constrain their effective use (ILO and World Bank, 2025). These patterns reflect persistent asymmetries in technological and institutional capacity between countries. Technological dependence is a key feature of many AI-adopting economies, where reliance on externally developed systems and infrastructures reflects broader asymmetries in knowledge production and technological capabilities (Ahmed, 2026).
AI implementation depends on broader organisational and institutional conditions, including infrastructure, regulation, and access to finance, which can facilitate or constrain the deployment of AI systems across firms and sectors (Bajwa et al., 2021, Arroyabe et al., 2024).
AI deployment is increasingly discussed alongside broader geopolitical and macroeconomic pressures rather than in isolation. Current global assessments note that ongoing conflicts, trade tensions, and financial vulnerabilities can weigh on growth and influence how new technologies spread, particularly in emerging and developing economies (IMF, 2026a). At the same time, IMF (2026b) suggests that the broader economic effects of AI will depend partly on how widely these technologies are adopted and on the institutional and infrastructural conditions supporting their diffusion across economies. Geopolitical risk can further constrain these dynamics by weakening cross-border supply chains and reducing the resilience of international production networks (Caldara and Iacoviello, 2022)

3.1 Integration of Artificial Intelligence across firms
Understanding the effects of artificial intelligence requires first examining how its adoption varies across firms and regions. Firms operating across both advanced and emerging economies are increasingly incorporating artificial intelligence into their operational models, primarily as a means of managing costs and sustaining productivity under competitive pressure. Recent data show that the use of artificial intelligence in firms has increased rapidly over a short period. In OECD countries, the share of firms using AI rose from 8.7% in 2023 to 20.2% in 2025 (OECD, 2026). A similar trend is observed in the European Union, where about 20% of enterprises reported using AI technologies in 2025, compared to 13.5% in 2024 (Eurostat, 2025). Importantly, this adoption is highly stratified by firm size, with more than half of large firms adopting AI compared to less than one-fifth of small firms, suggesting that AI may contribute to a key driver of structural divergence within the business landscape (OECD,2026).
Firm size plays a decisive role in shaping AI uptake patterns. Large firms consistently exhibit higher rates of AI integration than small and medium-sized enterprises, reflecting greater access to financial resources, data infrastructure, and specialised human capital (Filippucci et al., 2024; Lane and Saint-Martin, 2021). Digital technologies tend to reinforce scale advantages and widen performance gaps between firms (Brynjolfsson and McAfee, 2014).
As Acemoglu and Restrepo (2019) argue, automation technologies change the task content of production rather than simply eliminating labour, highlighting the central role of task reallocation mechanisms. Survey-based evidence indicates that firms adopting AI often report stable employment levels, with productivity gains primarily arising from process optimisation rather than headcount reductions (Filippucci et al., 2024; Lane and Saint-Martin, 2021). This reorganisation of tasks increasingly relies

on digitally mediated forms of coordination, reflecting broader trends in platform-based labour organisation (Hoinaru, 2025).

4. Methodological approach
The methodological approach examines the context of AI implementation as reflected in the academic literature and adapts these findings to the Romanian national case. To analyse the implications of AI, this research adopts a descriptive and interpretive approach based on secondary statistical data. The analysis focuses on identifying patterns of AI adoption and their potential implications for economic activity and labour market outcomes. Drawing on recent literature on AI uptake, the research uses secondary data related to the Romanian labour market, including labour market structure, employment patterns, educational attainment, and digital competences. The data are provided by institutions such as OECD, Eurostat, the World Bank, the European Commission, and the Romanian National Institute of Statistics and serve to examine economic implications, labour market developments, and patterns of technological change in Romania. This approach allows for the identification of potential challenges and risks associated with AI deployment from the perspective of Romania as a semi-peripheral, dependent market economy. In this context, the structural characteristics of the labour market allow for the examination of how AI integration interacts with existing employment patterns and labour market dynamics.

4.1 Romania as a dependent market economy
Romania's economic development can be understood within the framework of dependent market economies, being part of the Central and Eastern European economies that are deeply integrated into European production networks, while remaining strongly reliant on foreign direct investment and the presence of multinational companies (Nölke and Vliegenthart, 2009). In this context, EU integration has supported the growth of export-oriented sectors, including IT and business services, particularly outsourcing activities. (European Commission, 2020; World Bank, 2019; Drahokoupil, 2015), a development facilitated by relatively skilled labour, comparatively low labour costs, and the transfer of technology and organisational practices (Tarlea and Freyberg-Inan, 2018). Consequently, Romania combines participation in advanced manufacturing and digital services with continued reliance on foreign capital and ownership, suggesting an intermediate position within European production structures, often described in the literature as a semi-peripheral position (Jipa-Mușat, Prevezer and Campling, 2023).

4.2 Labour market challenges in Romania
The Romanian labour market maintained a relatively stable development, with the employment rate increasing from 62% to 66% between 2015 and 2019 (OECD, 2025). By 2024, employment reached approximately 5.7 million workers (INS, 2024), despite a contraction in the total labour force (World Bank, 2025). During this period, the transformation of economic sectors led to significant territorial and social mobility, particularly toward the expansion of the services sector and urban centres (INS, 2024). Over the past decade, continued labour market development was supported by increased external investment as part of Romania's broader process of European Union integration, as well as by the growing presence of large companies, which employ approximately 32.8% of the workforce (European Commission, 2024;

Marinescu, 2025). Despite these positive developments and productivity gains in certain economic sectors, several structural factors continue to shape labour market trajectories and may constrain further development, particularly in the context of ongoing technological change.
Although the general perspective on the labour market indicates progress and constant evolution, it has produced differentiated outcomes and a high concentration of economic activity in urban areas. These patterns have direct implications for income differences and employment opportunities and, by extension, for both internal and external mobility. While Romania's employment rate for the population aged 20–64 reached 69.4% (INS, 2025), it remains below the EU average of 76.2% in 2025 (Eurostat, 2025). At the national level, territorial disparities are even more pronounced, with employment rates of 76.3% in urban areas compared to 61.8% in rural areas (INS, 2025). Beyond employment rates, income structures reflect similar territorial differences, as earnings are closely linked to the spatial and sectoral distribution of occupations. According to data from the National Institute of Statistics (2026), higher-income activities are concentrated in sectors relying on advanced skills and capital investment, such as information technology, finance, and energy. By contrast, agriculture, hospitality, and peripheral service activities continue to be associated with comparatively lower income outcomes. Significant differences and patterns of polarization are indicated by net income levels that are up to four times higher, especially when compared with knowledge-intensive sectors such as information technology.
The observed differences indicate the fragile construction of the labour market, which is more visible from a social and economic perspective. Over time, this labour market structure has amplified patterns of internal migration towards urban centers, as well as external migration, because of the lack of qualitative employment opportunities at the territorial level. In recent periods, emigration patterns have moved towards more permanent forms (Baciu, 2018), amplifying other demographic pressures. Current estimates indicate that between 2024 and 2040, the active labour is projected to decline by approximately 15% (OECD, 2025). In response to persistent inequalities and emigration pressures, and with the aim of reducing the risk of poverty, recent years have registered successive increases in the gross minimum wage (European Commission, 2025). While this strategy has had a direct effect on wage levels, labour market competitiveness remains constrained by relatively high and weakly differentiated labour taxation (Dutcaș and Grosu, 2020). Recent developments indicate a slowdown in labour demand, reflected in a decline in the vacancy rate, with Romania recording one of the lowest vacancy rates among EU countries (0.6%) (Eurostat, 2026).

4.3 Education and lifelong learning in the Romanian labour market
Differences between rural and urban labour market conditions directly influence educational outcomes in Romania. Concerns regarding youth employment have driven recent policy interventions targeting NEET populations (not in employment, education, or training). More recently, these interventions have been expanded to include individuals up to the age of 30, with the aim of enhancing labour market integration (OECD, 2025). However, the outcomes of these measures reflect a long-term process and remain difficult to assess. Over the longer term in Romania, macro-level analysis examining the period 1991–2020 indicates a correlation between an increasing number of higher-education graduates and reductions in

unemployment (Dăncică et al., 2023). At the same time, the relatively low degree of mismatch between university specialisation and occupational placement (22%) suggests a generally favourable alignment between education and labour market outcomes (OECD, 2022). While this indicates a degree of structural progress, these improvements are concentrated primarily in urban areas. Nevertheless, such challenges persist, particularly in rural educational contexts characterised by limited household resources and lower school performance (Cristea, 2022). From this perspective, NEET status can be linked to social origin and is reflected in patterns of intergenerational educational mobility (Caroleo et al., 2022). This argument is supported by data for the population aged 25–64, among whom only 29% have attained a higher level of education than that of their parents (OECD, 2024).
These constraints are further reinforced by the limited engagement of the active workforce in digital skills development programs and with the National Employment Agency (NAE). As a result, Romania continues to rank last in the European Union in terms of basic digital skills. Despite additional resources allocated to education and teacher training, progress in digital skills development remains limited and uneven across educational stages (European Commission, 2025). Moreover, the ageing of the labour force, combined with limited progress in digital skill acquisition, constrains Romania's capacity to respond to ongoing technological development and to effectively valorise the population aged over 55 (Duminică and Hosszu, 2020).

4.4 AI Implementation: Risks and Implications for Romania

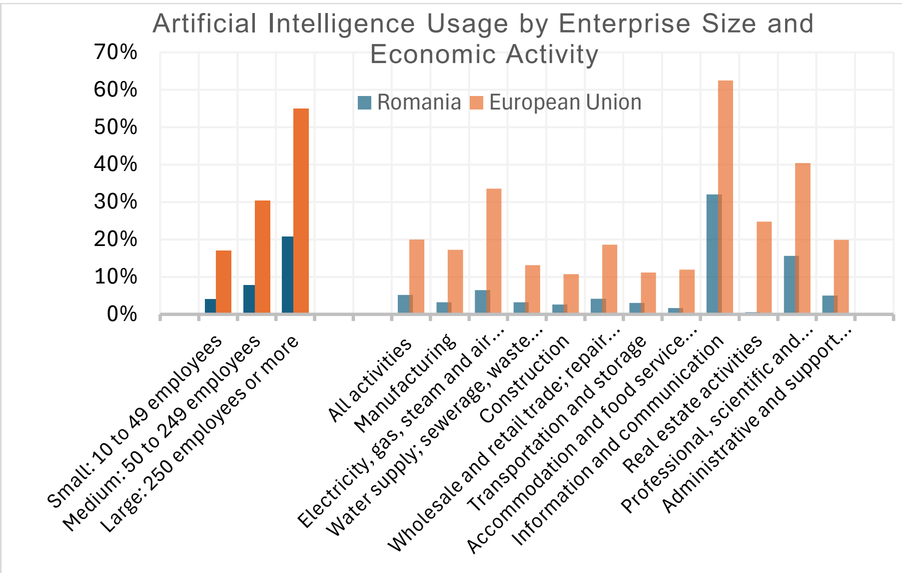

Figure 1: Artificial intelligence usage by enterprise size and economic activity
Source: Authors' adaptation based on Eurostat (2025) data on artificial intelligence by size class of enterprise and NACE Rev. 2 activity.

Analysing the current indicators of the Romanian economic and labour market context, several challenges related to AI adoption and diffusion can be identified, which operate through existing structural constraints and may further amplify uneven economic outcomes and reinforce social inequalities. Drawing on the main approaches in the academic literature on AI technologies, in line with descriptive data specific to the Romanian case, we identify a series of challenges that may be amplified.

(1) Slow adoption of AI technology in Romania. As shown in Figure 1, the adoption of AI technologies among Romanian enterprises (5.21%) remains significantly below the EU average (19.95%), both from the perspective of firm size and economic sectors. As indicated in the academic literature on uneven technological diffusion, delayed AI integration may amplify productivity gaps among companies operating in the Romanian market through slower task reorganisation and limited integration of digital processes. At the same time, the low integration of AI technologies limits the capacity of the labour market to absorb and develop specific competencies. (2) Dependence on external investment and outsourced service activities. The relatively low levels of AI deployment within Romanian enterprises may also be linked to the dependence on external investment and outsourced service activities. As the analysis reveals, this structure reflects the broader global division of labour, where lower value-added activities are more exposed to replacement through AI capabilities, particularly in externally controlled production structures. As AI is primarily implemented at the task level rather than across entire occupations, these segments are particularly vulnerable to automation, increasing exposure to employment insecurity and precarious work. This perspective is further amplified by the uneven distribution of AI adoption across firm size. In this context, although overall adoption remains below the European average (55.03%), AI diffusion in Romania is concentrated in large companies (20.75%), which employ approximately 32.8% of the national workforce. While this creates advantages for a particular segment of employees in accessing AI-related knowledge, it may also represent a source of instability in economic activity, particularly as large companies increasingly use semi-peripheral regions for cost optimisation. (3) Demographic structure. The literature indicates that AI uptake does not necessarily lead to immediate employment reduction, but during the transitional phase, it increases the demand for digital competencies. In this context, from a structural perspective, the ageing and decline of the Romanian labour force over the last decade may reduce the capacity to adapt to ongoing technological change. Given that AI integration requires continuous competence development, demographic pressures may act as a systemic constraint on adaptation by limiting the capacity to transition toward AI-complementary tasks. This perspective is currently visible in the limited engagement of the active workforce in digital skills development programs. (4) Labour market territorial fragmentation. Access to digital infrastructure, competencies, and technological capabilities remains uneven across regions, sectors, and types of companies. As a result, AI implementation reinforces existing territorial disparities between rural and urban areas, where employment rates stand at 61.8% in rural areas and 76.3% in urban areas, limiting opportunities for upward mobility. (5) Lower employment rates among young people. Limited access to stable employment pathways and to organisational contexts where AI-related competencies are primarily developed may reinforce long-term weakening of labour market integration. From this perspective, unequal exposure to technological environments can shape future career trajectories and contribute to persistent labour market segmentation by restricting access to high-exposure, AI-complementary work environments.

5. Conclusions

The article has examined the expansion of artificial intelligence within a broader context defined by economic uncertainty, structural transformation, and uneven global development. Rather than representing a single, disruptive break, AI emerges as a part of a longer trajectory of technological change that continues to reorganise production, labour relations, and firm behaviour. Under conditions of persistent inflation, tighter financial constraints, and geopolitical instability, firms increasingly turn to AI not primarily to replace labour, but to reorganise tasks, improve efficiency, and maintain competitiveness. This reinforces the view that the impact of AI is better understood at the level of tasks and organisational processes rather than in terms of aggregate employment displacement.

However, the adoption of AI remains highly uneven. Differences in firm size, access to capital, digital infrastructure, and human capital shape both capacities to adopt these technologies and the extent to which firms can benefit from them. As a result, these differences translate into unequal outcomes across firms and segments of the workforce. Workers possessing complementary skills are more likely to experience productivity gains and improved employment prospects, while those engaged in routine or lower-skilled activities face increased risks of labour market stagnation, displacement, or deteriorating job quality.

The case of Romania illustrates how these dynamics manifest within a semi-peripheral economy. While integration into European production networks and the expansion of service sectors have supported technological adoption, organisational constraints, such as regional disparities, demographic pressures, and limited digital skills, continue to shape labour market outcomes.

Taken together, the findings suggest that the impact of AI integration depends less on the technology itself than on the economic, institutional, and social context in which it is embedded. Without sustained efforts to address structural constraints, enhance skills and competencies, and strengthen institutional capacity, AI is likely to reinforce existing disparities rather than generate broadly shared economic benefits.

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