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Artificial intelligence and its socioeconomic impact: navigating the path between economic transformation and labor market disruption

Milorad Katnic^{a,b}, Ivana Katnic^{a,b,*}, Igor Luksic^{a,b}, Ivan Piper^c, Ilija Mugosa^{a,b}^a University of Donja Gorica, Faculty of International Economics, Finance and Business, Podgorica, Oktoih 1, Podgorica, 81000, Montenegro^b Center for Finance, Podgorica, Montenegro^c University of Donja Gorica, Faculty of Culture and Tourism, Podgorica, Oktoih 1, Podgorica, 81000, Montenegro

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ABSTRACT

The accumulation of human knowledge has been a key driver of civilization's progress. In recent decades, rapid technological advances, fueled by innovation and scientific research, have transformed the pace of change, creating new economic, social, and ethical challenges. Although fear of technological disruption has always accompanied progress, societies have repeatedly adapted and benefited from its outcomes. The rise of artificial intelligence (AI) now presents unprecedented opportunities and uncertainties, especially regarding its impact on work and economic structures.

This paper explores the socioeconomic implications of AI adoption in the context of sustainable economic growth and inclusive labor markets, focusing on Montenegro's evolving labor market amid tightening global resource and environmental constraints. Adopting a mixed-methods approach that integrates quantitative labor market analysis with a systematic review of international literature, the study examines how AI-related technological change influences employment levels, wage distribution, and patterns of economic growth. Using data from Montenegro's labor force survey (2018–2023) and relevant comparative datasets the research identifies associations between AI intensity and labor market outcomes, which are interpreted as descriptive rather than causal evidence given data limitations, underscoring the potential for AI to either exacerbate or mitigate social inequalities. The findings contribute to the growing body of evidence on the intersection of technology, labor, and sustainable development, and offer policy recommendations for leveraging AI to promote economic resilience, social inclusiveness, and long-term sustainability in small, resource-constrained economies.

1. Introduction

The rapid diffusion of artificial intelligence (AI) has intensified long-standing concerns about how technological change reshapes employment, wages, and the distribution of economic gains. While earlier waves of innovation raised productivity and created new jobs, they also displaced workers whose tasks were easier to automate, and AI now appears likely to deepen that pattern by affecting both routine manual work and some cognitive tasks. For transition economies, this issue is especially important because labor markets often adjust more slowly, institutional capacity is uneven, and policy responses are constrained by limited fiscal and administrative space. Montenegro provides a useful case because it combines a small open economy, a still-evolving

institutional environment, and a labor market that is exposed to external shocks and rapid technological diffusion.

This paper examines the socioeconomic implications of AI-related technological change in Montenegro, with particular attention to employment, unemployment, participation, and sectoral adjustment. The study asks three questions: what is the association between AI intensity and labor market outcomes, how do sectoral responses differ across the economy, and what policy lessons follow for inclusive adjustment? To address these questions, the paper combines a quantitative analysis of quarterly labor market data for 2018Q1–2023Q4 with a structured review of the relevant literature. The empirical contribution is deliberately cautious: given the short time span, the COVID-19 shock, and the difficulty of isolating AI from broader digitalization and

* Corresponding author. University of Donja Gorica, Faculty of International Economics, Finance and Business, Podgorica, Oktoih 1, Podgorica, 81000, Montenegro.

E-mail addresses: katnic@t-com.me (M. Katnic), ivana.katnic@udg.edu.me (I. Katnic), luksic@icloud.com (I. Luksic), ivan.piper@udg.edu.me (I. Piper), ilija.mugosa@centerforfinance.me (I. Mugosa).

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macroeconomic change, the results are interpreted as evidence of association and sectoral heterogeneity rather than strong causal estimates.

The paper contributes to the literature in three ways. First, it adds evidence from a transition economy that remains underrepresented in studies of AI and labor markets. Second, it links aggregate labor outcomes with sectoral patterns of adjustment, which helps identify where AI-related change is most likely to create gains or losses. Third, it uses the Montenegrin case to discuss how institutions, education, and policy capacity may mediate the effects of AI on employment and social cohesion. These contributions are intended to inform both academic debate and policy design in small economies facing rapid technological change.

To place these questions in historical context, it is worth recalling that it was only with the dawn of the modern era that the world economy experienced rapid growth after long periods of relative stagnation. Geographical discoveries, the expansion of global trade, an intellectual climate that encouraged freer interpretations of natural laws, accelerated scientific research, innovations, and Enlightenment political and sociological ideas collectively catalyzed accelerated technological advancement. At the same time, it should be acknowledged that scientific progress has also flourished in strongly religious settings—advances in astronomy and mathematics in fifteenth-century Central Asia are a notable example—so the relationship between religion and scientific progress is historically contested rather than uniform.

The Industrial revolution exemplifies this intersection of economic and technological progress. As emphasized by F. A. Hayek, the emerging social order was the unintended consequence of human interaction rather than deliberate design. The steam engine, initially invented to assist mining operations, became a catalyst for the global industrial transformation. Subsequent phases of development involving oil, the internal combustion engine, electricity, computers, and the rise of the Internet have dramatically reshaped the world over the past two centuries. Technology has endowed humans with near “superpowers,” enabling rapid travel over great distances, instantaneous communication across thousands of kilometers, exploration of the ocean depths, flight, and space travel. Machines extend human physical capabilities far beyond natural limits. For instance, agricultural machinery allows production on scales and speeds previously unimaginable, while modern transport moves large loads with greater efficiency than human or animal labor alone. Technology also amplifies intellectual capabilities, solving complex algorithms within seconds and storing vast data quantities that once required years and extensive physical space.

Many jobs have been transformed by technology. While some, especially those involving manual and routine tasks, have disappeared, replaced by machines, new and often higher paying roles have emerged. Technology has become indispensable in daily life and work. Yet, the question remains: does the advent of artificial intelligence (AI) represent merely another cycle of technological change, or does it constitute a fundamentally new development with the potential to radically transform society?

With the rise of new technologies, particularly generative AI, machines may increasingly rival humans not only in physical strength but also in a growing range of cognitive abilities, extending beyond routine tasks toward some forms of highly skilled work. AI is driving a profound transformation of labor markets characterized by both risks, especially for low- and middle-skilled workers, and opportunities for innovation and growth. The net effect on jobs and the distribution of AI's benefits will depend heavily on policy decisions, workforce adaptability, and investments in human capital. Ensuring equitable and inclusive strategies is essential to leverage AI as a force for societal well-being rather than division.

We stand at a crossroads where technology increasingly gains autonomy capable of working, creating, managing, and improving itself, potentially inventing ever more advanced technologies that could challenge human superiority. The transformations brought about by technology and AI, affecting both labor and daily life, are as remarkable

as they are daunting.

How will fundamental economic concepts like markets, resource allocation, and pricing evolve? This paper explores key aspects of AI's impact on human society, with a focus on labor and employment.

This research contributes to the existing literature by providing empirical evidence from the perspective of a small transition economy, addressing a notable gap in AI labor market studies, which have predominantly focused on developed countries. Using Montenegro as a case study, the paper examines how economies with limited technological infrastructure and developing institutional frameworks can navigate AI-driven economic transformation. Montenegro is a suitable case for several reasons. It is a small, open, service-oriented transition economy and an EU candidate country, with a labor market that has historically featured high structural unemployment and pronounced sectoral shifts. It has undergone rapid recent digitalization, including approximately 80% internet penetration and extensive 4G coverage while institutional and AI-governance capacity is still developing, which makes the mediating role of institutions directly observable. Quarterly labor force survey data are available from the Statistical Office of Montenegro for the full study period. Finally, Montenegro shares structural features with other Western Balkan and small transition economies, so the findings may inform a broader set of countries that remain underrepresented in the AI-labor market literature.

2. Literature review

To provide a clearer analytical structure, this review is organized around six themes that frame the empirical analysis: (i) the historical relationship between technological change and employment; (ii) task-based automation, displacement and job creation; (iii) inequality, polarization and distributional effects; (iv) the mediating role of skills, institutions and policy; (v) the distinction between AI and robotics; and (vi) evidence gaps concerning transition economies. A comprehensive survey of the economics of artificial intelligence is provided by [Lu and Zhou \(2021\)](#) ([Lu & Zhou, 2021](#)), which complements the thematic discussion below.

2.1. Historical perspective: technological fear and adaptation

Throughout history, technological advancements have repeatedly sparked fears and resistance, as communities faced job displacement and social disruption. More than two centuries ago, textile workers in England destroyed machines that threatened manual labor, and agricultural workers protested the introduction of tractors. Despite such resistance, innovations like electricity, internal combustion engines, telephones, computers, and the internet have significantly improved living standards and productivity while creating new employment opportunities. Historical patterns show that although some jobs disappear, new, often better-paying roles emerge, requiring different skills and knowledge. For example, shifts from agriculture to industry in the early 20th century caused temporary hardship but eventually led to broader economic growth and urban job creation. This cyclical nature of technological fear and adaptation helps frame contemporary concerns about AI and automation: while disruptions will occur, prior experience suggests opportunities for reskilling and economic transformation exist, provided effective policies and support systems are in place. Recognizing this historical context is essential for understanding AI's potential labor market impacts and guiding policy responses to foster inclusive growth.

The emergence of artificial intelligence (AI) is fundamentally reshaping labor markets, employment structures, and income distribution worldwide. This chapter reviews the current academic literature on the multifaceted impacts of AI on labor and employment, highlighting both opportunities and challenges.

2.2. Task-based automation, displacement and job creation

AI-driven automation is transforming industries by automating routine and, increasingly, non-routine cognitive tasks. This has led to significant job displacement, particularly in manufacturing, logistics, and administrative sectors, where studies report reductions in traditional middle-skill jobs by as much as 23–45% (Kanagarla, 2024; Liang et al., 2025; Maria et al., 2025). However, AI is also a powerful engine for job creation, generating new roles in AI development, human-AI collaboration, and digital transformation. For example, some sectors have seen a 31–60% increase in new employment categories, especially in healthcare, education, and technology (Kanagarla, 2024; Liang et al., 2025; Maria et al., 2025). The net effect of AI on employment is highly sector-dependent and skill-dependent, with high-skill workers benefiting most from new opportunities, while low-skill workers face greater risks of displacement (Belanche et al., 2024a; Liang et al., 2025).

2.3. Inequality, polarization and distributional effects

The literature reveals that AI adoption can both exacerbate and reduce income inequality, depending on context and policy intervention. In developed economies, AI has the potential to reduce wage inequality among most workers, but may leave the highest earners unaffected (Belanche et al., 2024a; Khan et al., 2024). In emerging economies, AI adoption can promote a more equitable distribution of corporate income when combined with investments in innovation and human capital (Fan et al., 2025; Wang & Jiao, 2024). However, without adequate policy responses, AI-driven job displacement risks widening the income gap, particularly for low-skilled and vulnerable groups (Kanagarla, 2024; Liang et al., 2025; Occhipinti et al., 2025).

2.4. Skills, institutions and policy mediation

A recurring theme is the critical need for large-scale reskilling and upskilling initiatives. The “adaptation gap” is significant: up to 42% of displaced workers face barriers to transitioning into new roles due to misaligned skill development programs and insufficient support infrastructure (Kanagarla, 2024; Maria et al., 2025). Proactive reskilling programs and targeted policy interventions—such as social insurance, education reform, and ethical AI governance—are essential to ensure equitable outcomes and mitigate negative effects (Joshi, 2025; Kanagarla, 2024; Karangutkar, 2023; Maria et al., 2025; Xu et al., 2024). Countries and sectors investing in these areas experience lower AI-induced unemployment rates (Maria et al., 2025; Xu et al., 2024).

AI's impact extends beyond employment, influencing economic growth, productivity, and public health through its effects on income distribution and job security (Liu & Liang, 2025; Occhipinti et al., 2025). The literature calls for integrated strategies that combine fiscal policy, regulation, and social policies to harness AI's benefits while mitigating risks, emphasizing the importance of collective well-being and sustainable development (Joshi, 2025; Occhipinti et al., 2025; Xu et al., 2024).

The effects of AI are not uniform across sectors. Manufacturing and retail experience high job displacement, while healthcare, education, and technology see greater job creation (Kanagarla, 2024; Liang et al., 2025; Maria et al., 2025). The demand for low-skilled labor is suppressed, while the need for middle- and high-skilled workers rises, with notable gender and regional disparities (Liang et al., 2025; Shen & Zhang, 2024; Skorobogatov & Sviridov, 2025).

It is also important to recognize concerns raised by some authors regarding AI adoption, including loss of privacy, cybersecurity threats, social isolation, biased decision-making, and lack of transparency and accountability, which can significantly harm users and organizations (Belanche et al., 2024b; Du & Xie, 2021; Puntoni et al., 2021). These scholars argue that AI implementations should be managed with strict ethical considerations and regulatory measures to mitigate risks and ensure responsible use, rather than solely focusing on performance and

innovation (Belanche et al., 2024b; Castillo et al., 2021; Wirtz et al., 2023).

2.5. Artificial intelligence and robotics: distinct but converging technologies

Throughout this paper it is important to distinguish between artificial intelligence and robotics. Robots primarily automate routine manual and physical tasks, whereas AI and generative AI in particular affects cognitive tasks, including some non-routine cognitive work. The two technologies are therefore distinct in their task content and in their likely labor market incidence, even though they are often discussed together. Their convergence, through the embedding of AI in programmable robots, is a potentially important development whose employment effects remain largely unexplored. Where the discussion in this paper refers to both technologies, this distinction should be kept in mind.

2.6. Evidence gaps and the case of transition economies

Our review identifies several critical gaps in the existing literature. The overwhelming majority of empirical studies focus on developed economies, particularly the United States and Western Europe, while limited research examines AI's labor market impacts in transition economies, despite their potentially different adjustment mechanisms and policy capacities. Additionally, most studies treat institutional factors as secondary considerations rather than central determinants of AI's labor market effects. Transition economies offer unique institutional contexts that may significantly influence how AI adoption affects employment and wages. While numerous studies propose policy interventions, rigorous empirical evaluation of these policies remains limited. Transition economies implementing AI-related policies provide natural experiments for assessing intervention effectiveness.

3. Methodology and data

Technological progress has consistently driven improvements in productivity and living standards, yet it also produces complex and sometimes contradictory effects on employment, wage distribution, and social dynamics. While technological advancements create new opportunities and increase productivity, they can simultaneously exacerbate wage inequality and displace specific groups of workers, particularly those performing routine or low-skilled jobs. This duality raises a fundamental question that underpins this and many other studies: Does technological progress lead to rising unemployment and poverty?

To investigate the relationship between technological progress and labor market outcomes: including unemployment, wage dynamics, and job polarization—a multi-method approach was adopted. This approach integrates quantitative, qualitative, and computational modeling techniques to capture the multifaceted impacts of technological change on labor markets comprehensively. The study synthesizes empirical data analysis, systematic literature reviews, and simulation-based modeling to enhance the robustness and depth of its findings (Goos, 2018; Jazdauskaite et al., 2021; Krstic, 2024; Lwenje & Silwimba, 2025; Myrzaliev et al., 2024; Ross et al., 2024a; Szabó-Szentgróti et al., 2021; Upreti & Sridhar, 2024). Data sources include both national and international datasets: labor force surveys, industry-level employment statistics, wage data, and various indicators of technology adoption, such as ICT capital stock, patent counts, and robot intensity measures, consistent with methodologies employed in other scholarly works (Berg et al., 2023; Ghodsi et al., 2024; Jazdauskaite et al., 2021; Myrzaliev et al., 2024; Rakhmetulina et al., 2023).

A structured literature review was conducted. Analytical methods included diverse econometric specifications, predictive modeling, and comparative methods, with rigorous screening for relevance, methodological quality, and study recency. Key challenges encountered involved

limited data availability, the rapid and evolving nature of technological innovation, and the inherent difficulty in capturing long-term and indirect labor market effects. The objective of the structured review was threefold: to identify the main channels through which AI affects labor markets (displacement, reinstatement, and productivity effects); to select candidate outcome, treatment, and control variables for the empirical model; and to derive testable expectations regarding sectoral heterogeneity. In this way, the review directly informed the empirical specification presented below.

This study employs a sequential explanatory mixed-methods design, combining panel data quantitative analysis with comparative case studies. This design facilitates the identification of causal relationships between AI adoption and labor market outcomes while accounting for institutional and contextual variables that mediate these relationships.

The three components of the design are integrated sequentially. First, the structured literature review establishes the conceptual framework and informs the selection of variables and hypotheses. Second, the quantitative analysis estimates the association between AI intensity and labor market outcomes in Montenegro and decomposes employment changes into displacement, reinstatement, and productivity channels. Third, qualitative and contextual evidence is used to interpret the estimates and to assess institutional readiness. The broader societal discussion in Section 6 draws on the structured review and on these secondary sources, not on the econometric estimates, and is intended to contextualize rather than extend the empirical results.

The core empirical framework utilizes a two-way fixed effects model, which controls for unobserved heterogeneity both across sectors and over time by including sector, time, and individual fixed effects. Specifically, the model is specified as:

$$Y_{ist} = \alpha + \beta_1 \text{AI_Intensity}_{st} + \beta_2 X_{ist} + \delta_i + \lambda_t + \theta_s + \varepsilon_{ist}$$

where Y_{ist} represents employment or wage outcomes for individual or group i in sector s at time t , AI_Intensity_{st} measures AI adoption in sector s , X_{ist} include control variables, δ_i , λ_t , and θ_s denote individual, time, and sector fixed effects respectively, and ε_{ist} is the error term clustered at the sector level. Potential endogeneity between AI adoption and labor market outcomes is an important concern: sectors experiencing stronger growth or greater institutional support may both adopt AI more rapidly and record better labor market outcomes, creating scope for reverse causality and omitted-variable bias. Instrumental variables based on historical technology adoption patterns and difference-in-differences strategies exploiting variation in adoption timing across sectors were explored; however, the short sample period and the COVID-19 shock limit the credibility of these strategies, and they cannot fully resolve endogeneity in a small and open transition economy. Accordingly, instrumental-variable and difference-in-differences estimates are not reported, and all estimates in this paper are interpreted as conditional associations rather than causal effects.

In terms of measurement, the dependent variables are the employment rate, the unemployment rate, and the activity (labor force participation) rate for the population aged 15 and over (2018Q1–2020Q4) and 15–89 (2021Q1–2023Q4), taken from the quarterly Labour Force Survey releases of the Statistical Office of Montenegro (MONSTAT); the unemployment series was additionally cross-validated against MONSTAT's consolidated LFS data file, with exact agreement in all overlapping quarters. Real GDP growth is the official year-on-year real growth rate from MONSTAT's quarterly national accounts. The baseline specification is estimated on aggregate quarterly observations by OLS with heteroskedasticity-robust (HC1) standard errors. In response to the reviewers' small-sample and overfitting concerns, the institutional quality indicator was removed from the specification, and the education index, the UNDP Human Development Report education dimension index, computed as the mean of expected years of schooling divided by 18 and mean years of schooling divided by 15, each capped at one is reported only as a robustness check, since it displays almost no within-

sample variation over six years.

The AI intensity index is constructed from two annual component series with complete and documented coverage for Montenegro: international exports and international imports of digitally-deliverable services (UNCTAD, accessed through the World Bank Data360 platform). Each component is min–max normalized over 2018–2023 and the index is the unweighted mean of the two normalized components, held constant within each calendar year at the quarterly frequency. Exports proxy the economy's digital production capacity, while imports proxy domestic absorption of digital services. Alternative components considered in earlier drafts (robot density, EU digital scoreboards) are not available for Montenegro over the sample period and are therefore not used. We acknowledge explicitly that this index captures AI-related digital transformation rather than AI adoption narrowly defined. The estimated coefficients should therefore be interpreted as reflecting AI-related digital transformation rather than the effect of artificial intelligence alone, and the revised paper uses this more cautious language throughout.

The sample period overlaps with the COVID-19 pandemic and with a major redesign of the Labour Force Survey. All specifications therefore include a pandemic-period indicator equal to one from 2020Q2 to 2021Q2, and a survey-redesign indicator equal to one from 2021Q1 onward, when MONSTAT adopted the new EU survey framework (Regulation (EU) 2019/1700); MONSTAT explicitly states that data from 2021 onward are not comparable with earlier years. Because pandemic-related dynamics cannot be fully separated from technology-related change over such a short window, results are interpreted with this caveat in mind.

Acemoglu and Restrepo (Acemoglu & Restrepo, 2018) provide the conceptual framework used to interpret the results, distinguishing displacement, reinstatement, and productivity effects of automation; a formal decomposition of Montenegrin employment changes along these lines is not performed, as the required task-level data are unavailable.

Regarding data sources, the analysis draws on Montenegro's labor market statistics, specifically quarterly labor force survey data from the Statistical Office of Montenegro (2018Q1–2023Q4), triangulated with administrative employment records obtained from the Central register of taxpayers and insured persons. For international benchmarking and comparative analysis, we incorporated OECD employment databases, Eurostat labor force statistics for EU candidate countries, and International Labor Organization (ILO) data. AI and technology adoption were proxied using OECD digital economy indicators and the WIPO global innovation Index.

We acknowledge that the relatively small sample size of 24 quarterly observations (2018Q1–2023Q4) could limit the statistical power and robustness of panel data estimates. Monthly data and extended temporal coverage, which might enhance analytical precision, were unavailable, as were more recent data. Despite these limitations, the chosen data sources and methods provide valuable insights into AI's labor market impacts within a transition economy context. In particular, with 24 quarterly observations the risk of overfitting is non-trivial, and the relatively high R-squared values reported in Section 5 should be read in this light. For these reasons, and given the identification concerns discussed above, all findings are framed as conditional associations rather than causal effects.

4. Historical and comparative perspectives on technological change and labor markets

This section situates the empirical analysis in a broader historical and comparative context. It draws on the structured literature review rather than on the estimates presented in Section 5, and its purpose is to motivate the sectoral hypotheses tested there and to inform the policy discussion in the conclusion. Readers primarily interested in the Montenegrin evidence may proceed directly to Section 5.

Berg, Papageorgiou, and Vaziri warn that over the past thirty years,

the ability of information and communication technology to substitute for unskilled workers has grown (Rakhmetulina et al., 2023). Greater substitutability of workers by machines and artificial intelligence increases wage inequality and the share of total income going to capital owners. As a result, greater productivity may emerge, but there may also be many losers, concentrated among those already earning lower wages. This transition may last decades.

Some researchers have warned of the overlooked negative sides of the industrial revolution. The first industrial revolution brought many improvements-including in agriculture. Better seed, fertilizers, and new, widely adopted mechanization meant much higher yields, but also a reduced need for labor. Overall, society became wealthier, agricultural products became higher in quality, more available, and cheaper. Still, agriculture's share in GDP and total employment has dropped significantly. Technology further spurred urbanization.

Illustratively, though controversially, Joseph Stiglitz in a 2011 article noted that as the U.S. shifted from an industrial to a service economy, it faced similar changes to eighty years earlier when technological revolution caused jobs to disappear from agriculture while new ones arose in industry (Stiglitz & Bilmes, 2011). Before the Great Depression, a fifth of Americans worked in agriculture. Technological changes reduced labor needs and increased production. Between 1929 and 1932, farm income dropped by a third. For many farm families, job loss and income loss meant inability to pay debts, problems for the financial sector, and less purchasing of industrial products creating a vicious cycle for the economy. Stiglitz argued that the shift from agriculture to industry seeded the Great Depression. However, attributing depression to urbanization and technological progress contradicts human aspirations and purposeful activity aimed at improving living conditions.

Industrialization, accompanied by the mass creation of urban jobs, was a remedy for farmers' difficulties, but it was a long and painful process. A similar process, according to Stiglitz, has taken place over the past 60 years in America, during which the share of industrial employment has dropped from one third to less than ten percent. The key reasons were higher productivity and globalization, which transferred many jobs to countries with lower wages. The results included income stagnation and job losses, but also more opportunities in less developed areas globally.

Rapid changes bring not only economic but political consequences as well. Additionally, social networks and their AI algorithms have already demonstrated how AI can influence major historical developments, mainly in Myanmar and Brazil, where Facebook and YouTube algorithms have led to emergence of extremism and populism with huge repercussions. Artificial intelligence brings changes so large and rapid that it is difficult to draw historical comparisons. In fact, technological substitution may encourage some anti-globalist actors to radically reduce migration trends.

The astonishing nature of recent trends is illustrated by the example of Netflix, which took 42 months to reach 1 million users. Facebook reached its first million users in 10 months, and when Instagram achieved 1 million active users in just three months, it was considered an unprecedented success. In contrast, ChatGPT, launched at the end of 2022, reached its first million users in five days and 100 million users in less than two months.

ChatGPT, an AI language model developed by OpenAI, accelerates and introduces new forms of change. It allows users to quickly edit text, translate languages, create reports, summarize texts, and prepare presentations. It responds to inquiries, generates ideas, programs, takes meeting notes, composes jokes, and can serve as a digital mentor for children or assist doctors diagnostically. AI applications in education and healthcare promote inclusion and improve service quality. Virtually no field of human labor remains untouched by ChatGPT's impact in its brief existence.

The potential is astonishing. Artificial intelligence enables tasks to be completed more quickly and cheaply, with less bureaucracy,

administration, verification, control, and even tax obligations. AI promises productivity gains and greater wealth generation alongside improvements in health and education. Nonetheless, the threat that AI may displace many human jobs grows increasingly pronounced.

Historically, technological change has typically led to the loss of lower-quality, lower-paid jobs, mostly held by unskilled workers. Simultaneously, new, higher-paying jobs requiring more knowledge and skills, often complementary to technology, have emerged. Today, approximately 60% of the workforce works in occupations that did not exist in 1940 (Hatzius et al., 2023).

With the rise of generative AI, the most threatened jobs are estimated to be highly paid intellectual roles, with developed countries facing greater pressure for job replacement. There is less incentive to automate low-paid manual jobs because such tasks are often more technically difficult and personalized, examples include hairdressers, cosmeticians, and masseurs. Conversely, AI and technological solutions can help less developed countries catch up in knowledge and accelerate economic growth and development.

In education, AI is making learning more accessible, engaging, and content-rich. Sal Khan, founder of Khan Academy, believes AI could bring transformative educational change, enabling every student to have a personal AI tutor and every teacher their own assistant. Khan Lab is developing AI infrastructure to realize this vision affordably. Educators can now tailor plans and materials to individual needs, including special-needs students, offering personalized lessons, faster responses, broader knowledge coverage, quizzes, games, and video content with adjustable pacing.

Professor Tyler Cowen, in his article from January 2024, imagines that AI will enable children to have digital friends as they want, communicate as much as they wish, and learn whatever they or their parents desire, including subjects like mathematics and science (Cowen, 2024). The learning model based on personalized digital companions may be the future. In this scenario, children will choose to spend time with digital friends, chatbots acting as interesting and entertaining companions encouraging enjoyable and straightforward learning.

According to a McKinsey study from 2017, by 2050, computers will be able to write better than humans, even surpassing the best writers (McKinsey Digital, 2023). Furthermore, by 2055, machines are predicted to be more creative than the most creative people. With ChatGPT's arrival, these timelines accelerated to 2024 and 2028. McKinsey also estimates that by 2045, 50% of human work activities will be automated, a decade earlier than previously thought.

The IMF analysis assumes that 40% of the global workforce will be affected by artificial intelligence. Estimated impacts are greatest in highly developed countries (60% of jobs affected), lowest in less developed countries (26%), with fast-growing economies at around 40%. Many less-developed economies lack the infrastructure and skills necessary to benefit from artificial intelligence, increasing the risk of growing inequality among nations. The analysis also notes that without state intervention, benefits from increased productivity will accrue primarily to capital owners, further increasing inequality.

Technology companies are leading these changes. They create, support, and invest in the development of artificial intelligence, while also being the first to alter processes and replace human jobs with algorithms, robots, and AI. Artificial intelligence is now used in literature, publishing, music, and photography. Increasingly, works, translations, and publications are created with AI, making it harder to distinguish what is human-made and what is generated by AI.

Concerns about job loss rise. A Franco-German survey of over 15,000 music creators and publishers found 71% of musicians see AI as a threat to their income and future. Over a third already use AI in music creation. A nearly six-month strike in Hollywood in 2023 ended with an agreement that studios would not use AI to write or rewrite scripts.

Goldman Sachs predicts that technological changes could displace 300 million jobs in the USA and Europe. A November 2023 Resume Builder survey of 750 business leaders found 53% of companies use AI,

24% plan to, and 37% have replaced employees with AI. Nearly half (44%) anticipate further job replacement in 2024, with 96% prioritizing AI skills when hiring.

Technological advancements, including AI and digitalization, generally boost GDP growth, productivity, and living standards over the long run. These benefits are strongest when technology augments skilled labor, leading to higher wages and new high-skill jobs (Bányai, 2024; Liang et al., 2025; Marguerit, 2025; Ross et al., 2024b). However, the benefits are not always evenly distributed, and the transition can be disruptive for some groups (Dosi & Virgillito, 2019; Ross et al., 2024a; Tyson & Zysman, 2022).

Automation and AI often substitute for routine and low-skilled jobs, leading to job losses in these sectors (Bányai, 2024; Dosi & Virgillito, 2019; Fossen & Sorgner, 2022; Goyal, 2020; Marguerit, 2025). The decline in routine work is gradual, with many affected workers managing to retain employment until retirement, but entry into these jobs is reduced (Kurer, 2020; Kurer & Palier, 2019).

Technology increases demand and wages for high-skilled workers while suppressing wage growth for middle- and low-skill workers, resulting in greater wage inequality and a shrinking middle class (Lee & Wie, 2015). The impact varies by sector and country, with some regions or industries experiencing more pronounced negative effects, especially where policy responses are lacking (Asaleye & Garidzirai, 2024; Gonese & Ngepah, 2024; Rymarczyk, 2020). The concentration of job losses and wage stagnation among certain groups can fuel political discontent, populism, and demands for protectionist policies (Broz et al., 2019; Finseraas & Nyhus, 2024; Katnic et al., 2024; Kipnis et al., 2022; Kunz et al., 2025; Kurer, 2020; Kurer & Palier, 2019; Levy, 2018; Malisic et al., 2025; Webb, 2019). The pace and management of technological change are critical in determining whether societies experience net gains or persistent inequalities.

5. Empirical results from Montenegro

In Montenegro, according to Damar survey from December 2023, understanding of artificial intelligence is low, yet fear is present (Resulbegovic, 2023). Six out of ten Montenegrins (59.1%) have heard of the term “artificial intelligence,” but less than a third understand it well (6%) or partially (25%). More than two thirds admit limited understanding (28.3%), while 40.2% claim no understanding at all. Only 27.2% had heard of ChatGPT, and less than 10% had used it. Among those who tried ChatGPT, top uses included information (28.4%), text creation and editing (23.3%), problem solving (22.7%), entertainment (19.9%), and language skill improvement (5.1%).

The Artificial Intelligence Landscape Assessment (AILA) for Montenegro, conducted by the UNDP (2025) in collaboration with the Chief Digital Office, evaluates the country's readiness to ethically and effectively integrate AI into public administration and the wider economy (United Nations). It highlights Montenegro's digital infrastructure strengths-80% internet penetration, extensive 4G coverage, a median population age conducive to digital skill development, and GDPR-aligned regulations. However, challenges include gaps in AI-specific skills, data interoperability, lack of cohesive AI strategy, and governance weaknesses. Montenegro ranks as “Systematic” for government AI usage, “Differentiating” for enabler roles, and “Opportunistic” for ethical AI.

Key findings indicate limited AI development in government, moderate data quality with interoperability issues, and significant technical and non-technical skill gaps. Despite strong infrastructure and funding for innovation, regulatory and inclusive AI frameworks need strengthening. Strategic recommendations include developing a government AI strategy, enhancing IT infrastructure and procurement, piloting AI projects, fostering public-private partnerships, expanding broadband and 5G, supporting AI startups and SMEs, and embedding ethical principles through accountability, inclusivity, safety, and transparency to advance Montenegro's Sustainable Development Goals.

Although AI awareness and ChatGPT usage are limited, fear of technology is widespread: 41% of Montenegrins fear job loss due to AI, and over a third are uncertain of its impact on their employment.

Montenegro's labor market exhibited significant dynamism during our study period (Perunovic et al., 2026). Employment rates increased from 45.0% in 2018 to 58.8% in 2023, while unemployment declined from 16.1% to 11.8%. However, these aggregate trends mask considerable sectoral variation that correlates with differential AI adoption patterns (see Table 1).

Our baseline estimates indicate a positive and statistically significant association between AI intensity and employment rates, as reported in Table 2. Specifically, a one-standard-deviation increase in the AI-related digital transformation index (0.33 units) is associated with an approximately 5.0 percentage point higher employment rate and a 4.8 percentage point higher participation rate, while the association with the unemployment rate (−1.4 percentage points per standard deviation) is significant only at the 10% level. Given the small sample of 24 quarterly observations, the overlap of the study period with the COVID-19 pandemic, and the breadth of the AI intensity proxy discussed in Section 3, these estimates should be read as conditional correlations rather than causal effects. The relatively high R-squared values in Table 2 may partly reflect overfitting in a short sample and should not be over-interpreted; two of the four regressors are event indicators absorbing known shocks rather than substantive covariates. The negative coefficient on contemporaneous GDP growth reflects the structure of the pandemic window: year-on-year growth in 2021 was dominated by base effects from the 2020 collapse, so the strongest measured growth coincided with still-depressed employment; the pandemic indicator captures the level of the shock, while the growth variable absorbs this rebound timing. Excluding the pandemic and survey-redesign indicators reduces the R-squared from 0.84 to 0.37 and renders GDP growth insignificant, underscoring that the two event indicators are essential to a well-specified model in this window. As a robustness check, adding the education index leaves the coefficient on the AI-related index essentially unchanged (15.4 to 16.1) but produces an unidentifiable education coefficient with a severely inflated condition number, confirming that slow-moving annual indicators cannot be separately identified over six years.

Limitations include the relatively short study period (2018–2023), which coincides with rapid AI development but remains early in the broader transformation. The COVID-19 pandemic's labor market shock during this period also complicates interpretation. Moreover, Montenegro's transition economy context may limit generalizability to other developing countries with different institutional environments. Furthermore, the analysis is conducted at the aggregate and sectoral level and therefore cannot speak directly to distributional outcomes across skill levels, wage groups, or demographic categories; statements in this paper concerning inequality and social cohesion should accordingly be understood as hypotheses grounded in the international literature rather than as findings of the Montenegrin analysis. The data also do not permit a decomposition of employment by routine versus non-routine (cognitive and manual) task content, which limits the ability to test task-based mechanisms directly. Finally, the instrumental-variable and difference-in-differences strategies explored here cannot fully resolve endogeneity—sectors experiencing stronger growth or greater institutional support may both adopt AI more rapidly and record better labor market outcomes—so reverse causality cannot be excluded.

Table 1
Descriptive Statistics, Montenegro, quarterly observations (2018-2023).

Variable	Mean	Std. Dev.	Min	Max	N
Employment rate (%)	48.1	5.1	38.5	58.8	24
Unemployment rate (%)	15.4	2.2	11.8	21.2	24
AI intensity index	0.45	0.33	0.05	1.00	24

Source: Authors' computations

Table 2

AI-related digital transformation and labour market outcomes in Montenegro, quarterly observations (2018–2023).

Dependent variable	(1) Employment rate	(2) Unemployment rate	(3) Participation rate
AI intensity	15.45*** (4.21)	−4.31* (2.15)	14.78*** (3.75)
GDP growth	−0.19*** (0.05)	0.03 (0.05)	−0.21*** (0.04)
Pandemic (2020Q2–2021Q2)	−7.90*** (1.37)	3.14** (1.12)	−7.52*** (1.26)
Survey redesign (2021Q1–)	−4.43* (2.47)	1.11 (1.23)	−4.28* (2.36)
Observations	24	24	24
R-squared	0.843	0.628	0.852

Notes: Standard errors (robust) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations

As a data note, four quarters of the employment and activity rate series (2021Q2, 2021Q4, 2022Q1, and 2022Q3) are derived from official population counts and year-on-year changes published in subsequent MONSTAT releases rather than from directly stated rates; the derivation is exact to within approximately 0.1 percentage point, and the corresponding unemployment rates match MONSTAT's consolidated data file in every case. The full data-source log accompanies the replication materials.

Future research should prioritize longer-term analyses, firm-level AI adoption studies, cross-country comparisons within transition economies, policy experiments, detailed distributional assessments across skill and demographic groups, and the construction of occupation-level measures distinguishing routine from non-routine cognitive tasks.

6. Broader societal implications of AI: contextual evidence and policy debates

This section complements the quantitative analysis with a qualitative discussion of the broader societal implications of AI. It is based on the structured literature review and on secondary contextual sources for Montenegro rather than on the econometric estimates in Section 5. Its purpose is to identify the societal and governance conditions under which the sectoral adjustments documented above are likely to be inclusive.

Technology is ubiquitous. People have become so dependent on technology that most cannot imagine life without it. Most people spend a majority of their free and working time in direct contact with technology.

Many wake up with their smartphones and spend much of their day and for some, much of the night, engaging with devices. By carrying smartphones, exploring social media platforms, making purchases and payments, countless personal data about habits and preferences is left behind. Each action becomes data, which can be used beneficially but also poses risks. Large volumes of data combined with machine learning assist in everyday life and solving problems but also influence individual decisions often without their awareness.

Abuse of data and the generation of false information to influence democratic processes and political systems, compromise individual privacy, etc., are some of AI's potential misuses. Dictators and malicious actors worldwide no longer need billions or vast infrastructure to carry out their plans. These acute issues have sparked demands for increased regulation. While additional regulation is inevitable, some argue there is also room for societal self-regulation, as in many other domains.

From the perspective of economic and social developments, the key question is the position of humans in the labor market and the kinds of activities through which people will earn livelihoods to remain functional participants in the market. Does the global fertility decline, occurring faster than earlier projections, imply the urgency of AI

integration to achieve economic system sustainability?

AI is bringing changes affecting livelihoods and work faster and more radically than any prior technology. AI's applications and reach are vast, with millions already captivated by ChatGPT's capacities shortly after its launch. New companies and jobs will be created rapidly with AI support.

At the same time, uncertainties and risks from AI use are significant. In ChatGPT's first year, millions of jobs and workplaces were impacted—entire industries face radical change. Jobs are replaced overnight by AI, and the labor market increasingly demands complementary AI knowledge.

From today's perspective, the skill to act as a bridge between AI and humans is increasingly valued. Those aiming to survive in the workforce, especially intellectual domains, must adapt quickly. Knowledge and use of AI and digital tools will become basic necessities. The job market will favor those curious and willing to learn. New wealth and value created with AI support have the potential to reduce poverty, increase living standards, health, and quality of life. Along this path, challenges and obstacles such as growing inequality, rising unemployment, and social tensions may increase.

7. Conclusion

This study provides exploratory empirical evidence on the association between AI-related digital transformation and labor market outcomes in Montenegro, a small transition economy undergoing digital transformation. By combining sectoral labor market data with international comparative insights, the study contributes to understanding AI's multifaceted socioeconomic effects in a transition-economy setting.

Our findings indicate that AI-related digital transformation is positively associated with aggregate labor market outcomes in Montenegro over 2018–2023: a one-standard-deviation increase in the digital transformation index (0.33 units) is associated with an approximately 5.0 percentage point higher employment rate and a 4.8 percentage point higher participation rate, while the negative association with the unemployment rate (about 1.4 percentage points per standard deviation) is significant only at the 10% level. These are conditional associations estimated on 24 quarterly observations spanning the COVID-19 pandemic and a survey redesign, and should not be read as causal effects. Sector-level estimates from the original submission were removed during revision because they could not be reconstructed from documented sources; sectoral heterogeneity is accordingly discussed as a literature-based hypothesis rather than an empirical finding of this paper.

Institutional quality is not included in the final specification, in response to the reviewers' small-sample concerns; the argument that governance, labor market flexibility, and education systems shape technological transition outcomes therefore rests on the international literature reviewed in Section 2 rather than on the Montenegrin estimates.

The transition toward an AI-enhanced economy presents unprecedented opportunities alongside significant challenges. Our research demonstrates that outcomes are not preordained by technology itself but depend heavily on policy choices, institutional resilience, and societal responses.

For Montenegro and similar transition economies, a key takeaway is that proactive preparation, strategic human capital investments, institutional strengthening, and robust social protection mechanisms can shape AI's impacts to benefit wide segments of society, rather than merely enriching already advantaged groups.

Given the rapid pace of AI development, policy windows for steering outcomes may be limited. Nations that act swiftly to enhance adaptive capacity, bolster institutions, and invest in their populations will be best positioned to harness AI's transformative potential while managing its disruptive effects.

CRediT authorship contribution statement

Milorad Katnic: Conceptualization, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Ivana Katnic:** Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Igor Luksic:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Ivan Piper:** Data curation, Methodology, Visualization. **Ilija Mugosa:** Data curation, Methodology, Visualization.

Statement for studies in humans/animals

This study did not involve human participants or animals. The research is based entirely on the secondary analysis of publicly available, aggregated statistical data published by the Statistical Office of Montenegro (MONSTAT), UNCTAD (accessed via the World Bank Data360 platform), and other official international sources, together with a review of published literature. No individual-level or identifiable personal data were collected, accessed, or analysed by the authors. Accordingly, ethical approval and informed consent were not required.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used ChatGPT-4, an AI language model developed by OpenAI and Claude Opus 4.8, primarily to improve readability, language clarity, and to conduct spelling and grammar checks. The AI tool also assisted in data processing and computational tasks related to the analysis. All tasks performed with AI assistance were subsequently reviewed, validated, and edited by the authors to ensure scientific accuracy and integrity. The authors take full responsibility for the content, interpretations, and conclusions presented in this publication.

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Milorad Katnic is full professor at the University of Donja Gorica (UDG), Montenegro. Prof. Dr. Katnic has served in various roles, including Finance Minister (2010–2012), President at Societe Generale Montenegro, and CEO of Podgorica Banka (OTP Group). He is Funder and Chairman at the Financial Solutions (FS), Montenegro. His interests include economic development, international economy, fiscal policy with presentations at institutions like Harvard and LSE.

Ivana Katnic is professor at University of Donja Gorica (UDG), Montenegro. She is the founder and CEO of the Center for Finance (CF), licensed scientific research organization in Montenegro. She has published numerous papers in various journals and held various national and EU-focused roles in education and research reform. Prof. Dr. Katnic's focus includes statistics, microeconomics, econometrics, academic writing, and methodological issues in research. Beyond research and teaching, she leads grant-funded projects and develops educational programs in finance and financial literacy. She is a member of the Society of Statisticians and Demographers of Montenegro.

Igor Luksic is a full professor at the University of Donja Gorica and a Senior Peace Fellow at the Public International Law & Policy Group. He served as Montenegro's Minister of Finance (2004–2010), Prime Minister (2010–2012), and Minister of Foreign Affairs and European Integration, overseeing the start of EU accession negotiations and the completion of WTO membership. Selected as a Young Global Leader by the World Economic Forum in 2013, he was Montenegro's official candidate for United Nations Secretary-General in 2016. From 2016 to 2021, he worked with PwC Southeast Europe on ESG strategies, sustainable finance, and public sector transformation. He serves on several international advisory boards, including that of the Boris Mints Institute at Tel Aviv University, is Co-Chair of the TOJOY Holding Group in Beijing, and co-founded TrustRock, a firm supporting investment and business development in Southeast Europe.

Ivan Piper is Assistant Professor at Faculty of International Economics, Finance and Business, and a coordinator at Faculty of Culture and Tourism, University of Donja Gorica. He holds PhD in cultural economics. As a PhD student and a scholarship holder of Ministry of Science of Montenegro, Mr. Piper took part in academic exchange programs in Indonesia and China. Ivan Piper has also worked as a researcher at Institute for Strategic Studies and Prognoses, where he was involved in conducting various quantitative and qualitative research projects, including data collection, data analysis and evaluation of public policies and strategies.

Ilija Mugosa, MSc, is a PhD candidate in International Economics at the Faculty of International Economics, Finance and Business, University of Donja Gorica, and Director of Research at the Center for Finance. Since 2026, he has also served as the representative of the European Institute of Innovation and Technology (EIT) for Montenegro, acting as the national contact point between Montenegrin innovators, researchers, and the EIT community. He previously served as Economic Policy Advisor in the Cabinet of the Prime Minister of Montenegro, where he coordinated the preparation of the Economic Reform Programme and the Fiscal Strategy and contributed to the introduction of performance-based budgeting. Earlier, as National Coordinator of the UNIDO Programme in Montenegro, he managed development projects on SME competitiveness, innovation, and resource efficiency, and coordinated the economic governance component of the UN Development Assistance Framework for 2017–2021. He began his career as a statistician at the Statistical Office of Montenegro (MONSTAT) and the European Commission (Eurostat), and since 2013 has lectured on International Financial Institutions and Business at the University of Donja Gorica.