ARTIFICIAL INTELLIGENCE AND THE PRODUCTIVITY PARADOX: MODELING STRUCTURAL TRANSFORMATION AND LABOR MARKET POLARIZATION ACROSS ECONOMIC GROUPS

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ABSTRACT

The active introduction of artificial intelligence into the work process causes significant changes in the labor market, accounting and management control systems, as well as in economic growth models. With the advent of new information technologies, it became obvious that national economies need to increase labor productivity through the process of digitalization. This requires scientific substantiation of energy-efficient technologies that affect the use of labor resources in terms of their effectiveness. The purpose of this research was to study the impact of artificial intelligence technologies on labor productivity and changes in the employment structure, especially in the context of the digital economy. The methodology was based on a systematic, logical-structural, comparative and econometric analysis of panel data for the period from 2018 to 2024. The analysis revealed that the introduction of automation, investments in human capital development and spending on scientific research and development have a statistically significant positive effect on labor productivity growth. An increase in the level of automation by 1% leads to a 0.44% increase in productivity, while an increase in spending on education provides an increase of 0.31%. In 2024, the average gross domestic product per capita in developed countries will be $ 133.2 thousand. In countries with economies in transition, this figure is $57.300, while in developing countries it is only $34.000. The digital integration index in developed countries is 0.85, while in developing countries it is only 0.52. The level of accounting automation in economically developed countries is 74%, while in less developed regions this figure is only 29%. The practical value of the results obtained lies in the formation of policies that contribute to the growth of labor productivity, the development of human resources and the improvement of management structures in the conditions of digital transformation.

Keywords: *Automation, Accounting, Control, Personnel, Digitalization, Management, Efficiency*.

1. INTRODUCTION

Artificial intelligence (AI) has had a significant impact on XXI century economic systems, transforming the way work is organized, human resources are managed, and approaches to accounting and control are taken. The introduction of AI into production and management processes helps to optimize resource use, improve decision-making accuracy, and open up new perspectives for assessing productivity [1–3]. In this context, digitalization and automation create new socio-economic challenges that require workers to quickly adapt to continuous technological development and

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reconsider the role of human capital in the process of creating added value [4, 5].

Scientific facts clearly indicate that the use of AI not only increases efficiency but also causes certain paradoxes in the economic sphere. Researchers have focused on a phenomenon known as the "productivity paradox", which is that the introduction of digital technologies does not always lead to increased labor efficiency [6–8]. On the other hand, there are opposing studies that suggest that intelligent technologies accelerate economic growth. They are also transforming the cost structure, changing approaches to human capital development, and revising the criteria for assessing employee productivity [9–11].

Various data show that automation leads to a decrease in the need for medium-skilled workers. Digital industrialization is creating new structural imbalances in the labor market that are not usually taken into account. This can lead to complex macroeconomic consequences [12–14]. As a result of these changes, it is important to make changes and introduce new approaches to performance measurement, human resource management, and accounting and control systems. Systems should facilitate intelligent interaction between people using the algorithm proposed by Dou et al. [15] and Yu et al. [16].

Although a lot of scientific data has already been accumulated in this area, there are still some questions that require more in-depth research. The scientific problem of this study lies in the lack of an integrated understanding of how the algorithmization of management processes changes the efficiency of accounting and control systems, how labor automation at the micro level affects macroeconomic productivity indicators, and what role human capital plays in a world where the autonomy of artificial systems is continuously increasing. These aspects become key to developing a comprehensive model that illustrates the relationship between technological innovations and labor efficiency. The scientific contribution of this work lies in a detailed study of how AI, acting as a powerful catalyst for change, affects labor efficiency. This phenomenon is viewed through the prism of managerial, accounting and macroeconomic processes. The significance of the study is determined by its theoretical contribution to understanding the relationship between artificial intelligence, labor productivity, and structural economic transformation, as well as by its practical value for improving personnel management, accounting, and control systems at enterprises.

The objective of the research was to identify the ways in which AI affects labor productivity, to determine which work processes are undergoing changes in the labor market and in accounting and control systems, and to assess what macroeconomic consequences these processes may cause. To achieve this objective, the following tasks were formulated: to identify which current areas of AI integration significantly affect the organization of labor; to analyze what specific effects artificial intelligence has in the field of accounting, control and personnel management; and to investigate how the implementation of automation processes affects employee productivity and how this is reflected in macroeconomic indicators. The originality of this scientific paper lies in the combination of economic methods for analyzing the impact of artificial intelligence, which allows us to consider technological innovations as a multifaceted factor that increases labor productivity and, at the same time, contributes to economic growth.

The research focuses on studying the relationship between the development of AI technologies, changes in labor productivity and transformations in the labor market within the framework of the digital economy. It was also planned to analyze the macroeconomic effects of these processes, taking into account new challenges for accounting and control systems. As for personnel management, it is necessary to solve several interrelated tasks to achieve the goal. Firstly, it is important to consider current theoretical approaches to the impact of AI on labor efficiency. Next, it is necessary to investigate how automation and algorithmization of processes affect employment, labor costs and productivity in different economic sectors.

In addition, the research aimed to assess the macroeconomic consequences of the use of AI, especially its impact on economic development, employment and social inequality. It was planned to study the impact of innovation, human capital and institutional capabilities on the formation of the volume of these consequences. It was important to create an analytical framework that could combine the results of microeconomic research on the implementation of AI with macroeconomic consequences. This contributed to increasing productivity, optimizing management processes and ensuring sustainable development of the labor market.

2. LITERATURE REVIEW

Current studies indicate a growing interest in the impact of AI on economic systems, particularly on labor productivity, employment levels, and macroeconomic stability. The existing body of research on artificial intelligence and its economic implications covers several interrelated areas, including the macroeconomic effects of AI and automation [17–21], labor market transformation and technological unemployment [14, 22–25], the use of AI in accounting, control, and management processes [26–29], and the impact of AI on labor productivity at the firm and sectoral levels [30–34]. Over the past decade, economic science has developed a variety of approaches to studying this issue. Some researchers consider AI to be a major driver of economic growth, while others argue that it leads to significant structural changes and may have a negative impact on the labor market. Economists have noted that artificial intelligence should be seen as an important driver of economic development. It both accelerates growth and contributes to changes that some people consider to be related to changes in the structure of the economy. Integration into well-regulated labour markets is more of a concern for European nations than the rate of technological advancement [17]. The scientist Acemoglu [18] analyzes the redistribution of income between capital and labor in the United States and considers the role of AI in this process.

From a macroeconomic perspective, it is important for scholars to understand the impact of AI on resource productivity and economic growth. Prettner and Bloom [19] point out that, analyzing economic data from the European Union, the positive impact of automation on production is possible only if there is a parallel increase in investment in human capital development. The United States economy demonstrates that without significant institutional changes, even an increase in overall productivity per capita can lead to a deepening of income inequality due to investment in new technologies [18]. Other scholars also express similar views and note that AI changes the vector of economic development ([20, 21].

In 2024, AI is an important element of economic structural change, establishing a certain balance between labor and capital. For example, a study by Tokunova et al. [21], focusing on post-Soviet countries in Eastern Europe, notes that social adaptation to automation is inferior to that observed in Western Europe. Several studies in this area focus on labor issues. Authors Nguyen and Vo [14], George [22] and Özer et al. [23] examine the development of technological unemployment and labor structure in the context of trends in the impact of digitalization on the work process, which increases the demand for skilled professionals. Lazaroiu and Rogalska [24] examine the phenomenon of "partial substitution" of work processes, which occurs when AI performs analytical and managerial functions, but human labor remains necessary. This finding supports the adaptation theory put forward by Fatima et al. [25], which emphasizes the importance of adapting to technology and the role of developing digital skills in workers.

The integration of AI into accounting alters the logic of control, as demonstrated in the study Rawashdeh [26], which examined the Middle Eastern countries. It gradually shifts from the conventional retrospective method to proactive, preventive analysis. Similar conclusions are demonstrated by the authors Obaydin et al. [27], who, analyzing Australian companies, prove that a system of precise algorithms significantly increases the effectiveness of internal control and significantly reduces the risk of management errors. According to the results of the study by Hammad [28], dedicated to Sudanese enterprises, intelligent analytical platforms not only increase the accuracy of financial assessment but also make reporting as "transparent" as possible. Similar conclusions were made by Ali et al. [29] in the analysis of South Asian companies, where AI systems are skillfully intertwined with cost control and strategic management, creating synergies between operational efficiency and long-term strategy. In accounting practice, artificial intelligence is no longer limited to automation – it is capable of performing highly intelligent audits, relying on machine learning.

Another issue that is being actively studied is the impact of artificial intelligence on labor productivity. Scientists Damioli et al. [30], analyzing EU enterprises, found that the implementation of AI technologies significantly increases the efficiency of small and medium-sized firms, and Noy and Zhang [31], taking into account experimental data from the United States, showed that the use of generative AI speeds up the performance of work mental tasks by approximately 14%. A study conducted by Necula et al. [32] analyzed the Romanian business sector, where it was found that the positive effect of the use of AI is manifested only when the organization already has a developed digital corporate culture (at least at the initial level). However, this impact is not unconditional: in the case of low readiness or the absence of an appropriate digital culture, productivity can decrease. The impact of AI is mediated, and its strength depends on how actively teams share knowledge and are willing to learn new abilities, according to a study by Shaikh et al. [33] based on data from Pakistani organizations. In the Chinese context, Gao and Feng [34] documented a similar pattern. According to their data, there is a so-called "efficiency threshold" – a limit beyond which technological innovations no longer undermine, but rather increase, productivity.

In the modern international scientific environment, an interdisciplinary approach that integrates economic analysis and behavioral aspects is becoming increasingly actively studied. In the study of Aoujil and Hanine [35], devoted to the economies of North Africa, artificial intelligence acts as a driving force for new models of economic behavior that radically rethink the structure of consumption and mechanisms of accumulation. Scientists Zhou et al. [36], analyzing data from Asian countries, emphasized that AI is able to stimulate growth in gross domestic product (GDP) with a simultaneous increase in asymmetry in income distribution. Similar conclusions were made in China by Qin et al. [37], proving that the effect of AI cannot be simply divided into homogeneous components and directly affects all components of the work process.

A critical review of the literature shows that existing studies rely on several main methodological approaches, including macroeconomic modeling [18–21], firm-level empirical analysis and experimental designs [30–34], survey-based studies [32, 33], and case studies of accounting and management practices [26–29]. These approaches have significantly expanded understanding of the role of AI in economic development; however, they also have important limitations. In particular, macroeconomic studies often do not capture the organizational and managerial mechanisms through which AI affects productivity [18–21]; firm-level and survey-based studies usually focus on specific sectors, countries, or firms and therefore have limited generalizability [30–34]; and accounting- or control-oriented studies typically examine internal process improvements without linking them to broader labor market and macroeconomic outcomes [26–29]. As a result, the relationship between micro-level automation, changes in accounting and control systems, and cross-country differences in labor productivity remains insufficiently integrated within a single analytical framework. The proposed approach in this study is intended to address these limitations by combining comparative macroeconomic analysis, panel-data econometric assessment, and the consideration of management, accounting, and labor-market dimensions within one research design. Such an approach makes it possible to assess not only the productivity effects of AI, but also the structural transformation of employment and the institutional conditions that shape these effects across different groups of economies.

3. METHODS

The basis of the present research is a systemic, interdisciplinary and comprehensive approach. This approach combines methods of economic theory, macroeconomic analysis, management accounting and statistics. The research was designed as a comparative analytical study combining conceptual, descriptive, and econometric methods. The study is analytical and theoretical in nature and is based on the integration of logical, empirical and quantitative analysis. Reports and statistical data from international labor economics and innovation organizations served as the foundation. A logical-structural approach, which enables the identification of the relationship between technical advancements, employment, and economic progress, was employed to investigate the effect of artificial intelligence on labor productivity. The abstract-logical approach made it possible to determine the main theoretical principles, while analysis and synthesis were used to summarize the results of previous studies and identify the main trends.

This research covers the period from 2018 to 2024. During this period, the global economy has undergone major structural changes caused by the active use of artificial intelligence technologies in production processes, management, the service sector and financial analysis. This stage is characterized by the transition from test models of using algorithms to the full integration of AI into accounting, control and human resource management systems. In order to ensure the relevance of the analysis, the data were classified into three categories of economies: advanced countries (the USA, Germany, France, Japan, South Korea), countries with economies in transition (Poland, the Czech Republic, Romania, Turkey, Ukraine) and developing countries (India, Indonesia, Brazil, Mexico and Vietnam). Accordingly, the analytical sample included 15 countries divided into three comparative groups of five countries each. This grouping made it possible to compare differences in digital maturity, organizational capacity, and human capital composition, as well as

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to identify variations in the impact of AI on labor productivity, accounting, and management control systems across different economic contexts.

The statistical analysis was conducted based on international sources, including the World Bank's World Development Indicators [38], the OECD Digital Economy Outlook 2024 [39], the Global AI Index [40], and the World Economic Forum's Future of Jobs Report 2023 [41]. An econometric approach was applied for the quantitative analysis, using panel data for the period 2018-2024. This allowed us to identify statistical relationships between the integration of AI technologies and changes in labor productivity. The implementation of the research methodology involved several sequential stages. First, comparable statistical indicators were selected from international databases according to their relevance to labor productivity, digitalization, employment structure, innovation activity, and AI diffusion. Second, the data were grouped by country category in order to ensure cross-country comparability. Third, descriptive and comparative analysis was conducted to identify differences in the main economic and structural indicators across the three groups of countries. Fourth, a panel regression model was estimated to assess the statistical relationship between AI-related factors and labor productivity. Finally, the obtained results were interpreted from macroeconomic, labor-market, and management-accounting perspectives. The independent variables included: investment in scientific studies and developments, the index of digital transformation of the economy, the share of education spending in total GDP and the level of automation of processes. Structural features of the labor market were also studied, in particular, the proportion of high-tech vacancies and changes in the professional structure by different categories (routine, analytical and technical). This illustrates the evolution of labor roles under the influence of artificial intelligence. The innovation index and the volume of investment in this technology were also taken into account, which reflect both the institutional and technological capabilities of economies.

According to the OECD [39] grading, the digitalization index was divided into four key categories: low (up to 0.30), medium (from 0.31 to 0.60), high (from 0.61 to 0.80) and very high (from 0.81 to 1.00). These categories determined the level of digital maturity of the economy. According to Stanford HAI [40], the innovation activity index was also classified into four categories: low (up to 0.40 inclusive), moderate (from 0.41 to 0.65), high (from 0.66 to 0.85) and very high (from 0.86 to 1.00). In this study, these indicators are given as relative changes – Δ 2018-2024 in percent. This demonstrates the dynamics of change, which covers the following aspects: labor productivity, employment composition, digitalization index, innovation process index. Other aspects, such as the share of education and R&D spending in GDP, as well as the volume of investment in artificial intelligence, are presented as averages as of 2024. In the econometric specification, labor productivity was used as the dependent variable, while the independent variables reflected the main dimensions of AI-related transformation: process automation, human capital investment, research and development expenditure, digital integration, and the share of high-tech employment. In order to quantify the impact of artificial intelligence technologies on labor productivity, a panel regression model with the following structure was developed:

$$LP\_i=\alpha+\beta_1\ AI\_i+\beta_2\ HC\_i+\beta_3\ R\&D\_i+\beta_4\ DI\_i+\beta_5\ EM\_i+\varepsilon\_i, \quad (1)$$

where: LP – labor productivity; AI – level of process automation or share of enterprises using AI (%); HC – human capital (education spending in GDP, %); R&D – investment in research and development (% of GDP); DI – digital integration index (0-1); EM – share of high-tech employment (%); ε_i – stochastic residual reflecting the influence of unaccounted factors; α – constant (free term) showing the basic level of labor productivity in the absence of the influence of independent variables; β_1, β_2, β_3, β_4, β_5 – model parameters that reflect the marginal impact of each independent variable on the dependent variable. The statistical significance of the regression coefficients was determined using Student's t-test, with the significance threshold set at $p < 0.05$. The use of panel data made it possible to trace changes over time and to compare the strength of the identified relationships across different groups of economies within a unified analytical framework.

Structural and functional analysis was used to study the mechanisms of AI's impact on internal accounting, audit and control processes in organizations. In addition, the study of the content of international reports made it possible to identify the main trends in the digital transformation of management practices. The use of both inductive and deductive approaches contributed to the formulation of hypotheses based on empirical data and their verification within the framework of the analytical model. Thus, the applied methodology combined theoretical generalization, comparative cross-country analysis, and econometric testing, which ensured a consistent assessment of the impact of artificial intelligence on labor productivity, employment structure, and the effectiveness of management control in a global context.

4. RESULTS

Labor productivity and the effectiveness of using artificial intelligence directly depend on technological progress in economies, the amount of investment in human capital and the state of digital infrastructure. In order to interpret the results, average values were calculated for six criteria: gross domestic product per employee, the percentage of companies using artificial intelligence, the amount of investment in research and development, as well as the share of spending on education, the digital integration indicator and employment in the high-tech sector (Table 1).

Table 1: Key indicators of economic development and digital integration of countries

Group of countries	GDP per person employed, 2024 (PPP $, 2021)	Δ 2018-2024, %	Share of enterprises using AI, % (2024)	R&D in GDP, %	Education in GDP, %	Digital Integration Index (0-1)
Advanced countries (the USA, Germany, France, Japan, South Korea)	133 200	+12.5	64	3.0	5.2	0.85
The countries with economies in transition (Poland, the Czech Republic, Romania, Turkey, Ukraine)	57 300	+17.6	48	1.7	4.4	0.66
Developing countries (India, Indonesia, Brazil, Mexico and Vietnam)	34 000	+18.0	29	1.1	3.3	0.52

Source: compiled based on the summary of data from the World Bank [38], OECD [39], World Economic Forum [41]
Note: All indicators are presented as average values for groups of countries by level of economic development. Δ 2018-2024, % reflects the growth rate of the indicator over the period under study. The digitalization index varies from 0 (minimum digital integration) to 1 (full digital maturity)

In 2024, a significant gap between countries in terms of productivity, digitalization, and investment in human capital is observed. In advanced economies, the average gross domestic product per employed person is $133.200 in purchasing power parity (PPP), while in transition economies it is only $57.300. In developing countries, it is only $34.000 [38]. This difference both indicates disparities in technological development and reflects deeper structural inequalities in productivity and labor efficiency. In addition, growth rates between 2018 and 2024 are highest in less developed economies (+17.6-18.0%), indicating a process of technological "catch-up" and a late-adoption effect. This means that new technologies are introduced more quickly due to the absence of outdated infrastructure. At the same time, these higher growth rates should not be interpreted as evidence of a stronger overall AI effect in developing economies, since they are observed from a substantially lower initial productivity base. This pattern points to asymmetric modernization, in which relative growth is faster but absolute economic and technological gaps remain substantial.

The percentage of companies using AI varies from 64% in advanced countries to 29% in developing countries [39]. This illustrates the different levels of digital maturity: advanced countries are at the stage of integrated management based on analytical data, while others are only starting to implement individual algorithmic components. The Digital Integration Index (0.85 vs. 0.52) shows a significant lag in automation. R&D spending, which is 3.0% of GDP, and education spending of 5.2%, indicate that technological efficiency in advanced countries depends on stable investments in knowledge and human capital development. In contrast, their insufficiency in developing countries slows down the process of digital transformation and limits the potential for economic growth. For a more detailed analysis of labor productivity, structural characteristics were studied. They reflect the degree

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of innovation, automation of management processes and changes in employment in high-tech industries (Table 2).

Table 2: Key structural indicators of employment, innovation and automation of countries

	Share of high-tech employment, % (2024)	Δ 2018-2024, p.p.	Automation of accounting and control, % of enterprises (2024)	Innovation activity index (0-1)	Investments in AI, billion $ (2024 estimate)
Advanced countries	17.4	+3.6	74	0.88	118
The countries with economies in transition	9.3	+2.1	51	0.64	22
Developing countries	5.4	+1.5	29	0.46	12

Source: compiled based on the generalization of data from the World Bank [38], OECD [39], Stanford HAI [40]
Note: indicators are given as average values for three groups of countries formed by the level of economic development. Δ 2018-2024, p.p. reflects the change in the indicator in percentage points over the period under study. The innovation activity index varies from 0 (low level of innovation potential) to 1 (high level of innovation)

Table 2 illustrates that the percentage of high-tech workers in advanced economies increased by 3.6 percentage points from 2018 to 17.4% in 2024. This increasing displacement of routine jobs points to a demand for analytical and information technology (IT) as well as engineering skills. The growth is up to 9.3% for transition economies (Poland, Czech Republic, Romania, Turkey, Ukraine), and less than 5.4% for developing countries. These findings suggest that structural labor market renewal requires a strong innovation base and investment in education, which have so far been limited in less developed countries. Automation in accounting and control is 74% in advanced countries, 51% for transition economies and 29% for developing countries, indicating uneven digital maturity of economies. The high level of automation for developed economies is driven by stable institutions, access to capital and developed data infrastructure, compared to the fragmented and partial degree of automation for transition economies.

For advanced, transition and developing economies, the innovation activity index is 0.88, 0.64 and 0.46 respectively, indicating an almost two-fold difference between the extreme groups. A higher index indicates both a higher share of innovative enterprises and the ability of the economy to generate new knowledge and technological solutions. The intensity of investment in AI also reflects a global asymmetry: $118 billion spent by advanced economies compared to $22 billion spent in transition economies and $12 billion spent by developing economies. The concentration of investment increases the technological dependence of less developed economies on centers of innovative economic development and the corresponding risks of technological divide are increasing. The findings show that AI is now a systemic factor in structural modernization, but it has an uneven impact. In transition economies, these factors point to opportunities for faster development if appropriate public policies are focused on promoting innovation, digital education and institutional strengthening of the labor market. Thus, the comparative results indicate that the productivity effects of AI are strongest where automation is supported by complementary institutional conditions, especially investment in education, research capacity, and digital infrastructure.

The global labor market transformation in 2024 marked a significant reform of the employment structure under the influence of AI technologies. The introduction of automation and digital tools led to the reduction of routine professions and the creation of analytical, technical and creative work models. Figure 1 shows the distribution of different fields of work by career type in countries with different degrees of economic progress: the relative technological level and degree of labor market maturity in advanced, transitional and developing countries.

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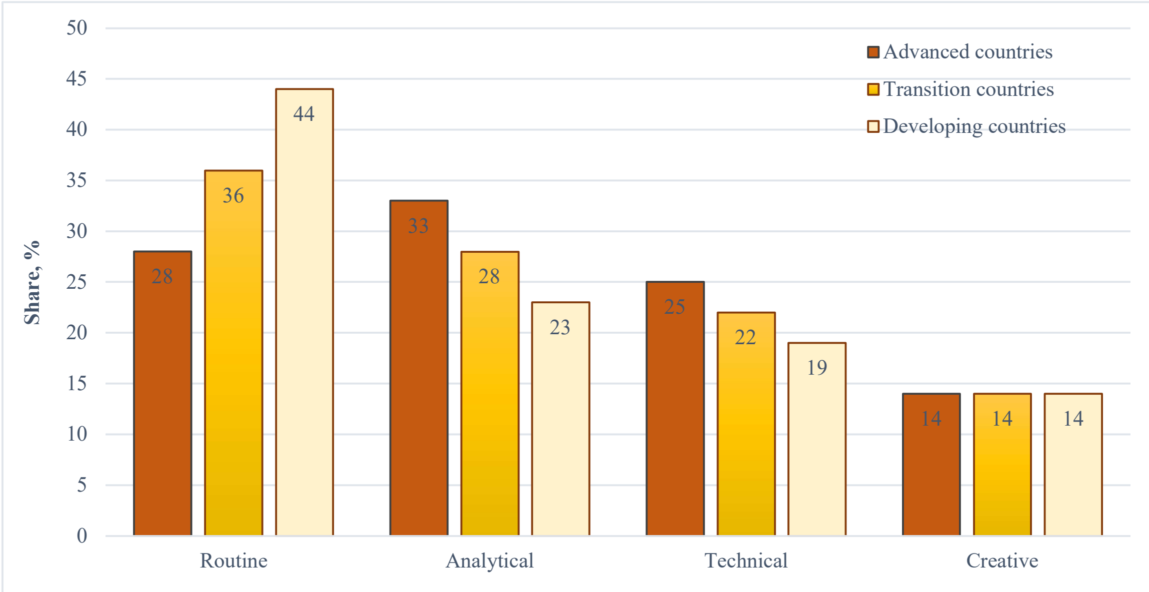

Figure 1: Change in employment structure by professional categories in 2024
Source: compiled by the author based on data from the World Economic Forum [41], OECD [39], World Bank [38]
Note: indicators are averaged for a sample of countries divided by level of economic development

Figure 1 illustrates the clear polarization of occupational employment patterns across countries' levels of economic development. Even in advanced countries, the share of routine jobs is estimated at only 28%, while the share of analytical and technical occupations exceeds 58%, with both occupations at 33% and 25%, respectively. This suggests that AI technologies are deeply integrated into the economy, and the workforce is moving towards data processing, automation and the management of complex data systems. In transition economies, the situation is intermediate: routine jobs account for 36%, while analytical occupations account for 28% and technical jobs for 22%. This suggests structural convergence towards advanced countries, while digital adaptation is slow due to limited funding for innovation and insufficient development of educational infrastructure. In developing countries, routine work continues to dominate (44%), with the share of analytical and technical professions at 23% and 19%, respectively. This indicates that the application of AI in these economies is mostly local and does not have a systemic impact on the labor market. Despite the lack of variability in creative professions (14% across all groups), it is the analytical and technical areas that determine the technological maturity of any economy. As a result, digitalization and the development of artificial intelligence in tandem lead to a gradual transition from a physical to a smart economy. An important result is that labor-market transformation is not uniform across occupational categories. While analytical and technical occupations expand with increasing digital maturity, creative occupations remain stable across all country groups. This suggests that the current phase of AI diffusion primarily restructures routine and knowledge-intensive work, whereas creative functions remain comparatively less differentiated at the macro level.

In order to confirm the established interconnections between the implementation of artificial intelligence, human capital formation and labor productivity, a panel regression model was developed based on Tables 1 and 2 for three groups of countries (Equation 1):

$$LP_i = 0.68 + 0.44AI_i + 0.31HC_i + 0.17R\&D_i + \varepsilon_i$$

The obtained coefficients indicate significant positive effects of automation ($\beta_1 = 0.44$), investment in human capital ($\beta_2 = 0.31$), and R&D spending ($\beta_3 = 0.17$) on labor productivity growth ($p < 0.05$). This means that a 1% increase in investment in AI technology will lead to a 0.44% increase in productivity, while a 1% increase in education spending will lead to an additional 0.31% growth. Thus, the model shows that technological automation, human capital formation, and economic efficiency are indeed interrelated. Among the estimated factors, automation demonstrates the strongest coefficient, which indicates that the direct diffusion of AI-related technologies is the most influential predictor of productivity growth within the proposed model. At the same time, the positive coefficients for human capital and R&D suggest that the productivity effect of AI is not autonomous, but depends on complementary investments in education and innovation capacity. Therefore, the model performs better in economic environments where technological adoption is reinforced by institutional readiness, whereas in less digitally mature contexts the same mechanisms are weaker because automation is implemented more fragmentarily and with lower absorptive capacity.

The results show that AI technologies, when implemented in a number of enterprises, have a multifaceted impact that goes beyond simply increasing the productivity of any one enterprise. Based on automation, increasing labor efficiency causes a structural reformatting of the labor market: a decrease in the number of routine professions and an increase in the need for highly qualified specialists in data analysis, programming, human resources management and digital systems. At the micro level, this can be seen in the change in accounting and control functions – they are moving to an analytical role, moving from recording facts to tools for forecasting and strategic planning. At the macroeconomic level, increased automation, investment in human capital and increased investment in research and development have statistically significant and economically tangible multiplier effects, stimulating economic growth and innovation, especially in advanced countries with the highest levels of digital maturity. Meanwhile, in transition and developing countries, the impact of AI is limited by insufficient institutional capacity and underdeveloped innovation capabilities. This highlights that the new function of artificial intelligence is not only a factor in increasing efficiency but also a factor of (macroeconomic) differentiation, with new challenges for employment policy, public administration and labor market accounting and control systems. At the same time, the results reveal several mixed patterns that are important for interpretation. First, less developed economies demonstrate higher relative growth rates despite substantially lower absolute productivity levels, which reflects a catch-up effect rather than technological leadership. Second, the persistence of a constant share of creative occupations across all country groups indicates that not all segments of the labor market are transformed at the same pace. Third, transition economies occupy an intermediate position in almost all indicators, which suggests that partial digital adaptation does not automatically translate into proportional productivity gains. These patterns show that the effects of AI are differentiated, context-dependent, and conditioned by the broader institutional and investment environment.

5. DISCUSSION

The results suggest that the adoption of AI technology has a sustained positive effect on labor productivity, but the structure of this effect is heterogeneous and spatially and geographically diverse. In 2024, GDP per person employed averaged \$133.2 thousand in advanced countries, \$57.3 thousand in transition countries, and \$34.0 thousand in developing countries, growing by +12.5%, +17.6%, and +18.0%, respectively, over the period 2018-2024, reflecting a combination of a high starting base effect in developed economies and a "catch-up" effect in less developed ones. This is consistent with Yang's [42] finding that, relative to initial investment and institutional support, the effect of AI on productivity is stronger when there is sufficient investment and institutional support. This is supported by Al Naqbi et al. [43], who found that generative AI can improve productivity where appropriate digital contexts exist.

Panel regression based on the identified data showed the existence of a statistically significant positive relationship between automation, investments in human capital and spending on research and development, which contributed to the growth of labor productivity ($\beta_1=0.44$; $\beta_2=0.31$; $\beta_3=0.17$; $p<0.05$), which indicates the interaction of technological and educational and innovative factors. This scenario is consistent with Patil's [44] conceptual findings that the cumulative effect of AI in the long term only manifests itself through synergistic investments in technology, staff skills, and the institutional environment, and is also consistent with the approaches of Olan et al. [45], who emphasized the contribution of organizational learning and knowledge sharing to AI-driven productivity gains. In this sense, the results obtained confirm that accounting and control are no longer just recording functions, but are becoming a fundamental part of performance management. At the same time, the obtained results indicate that the proposed analytical approach works better in economies where AI adoption is accompanied by institutional readiness, stable investment in education, and stronger innovation capacity. In such contexts, automation is not an isolated technological intervention, but part of a broader system that includes digital infrastructure, absorptive capacity, and organizational adaptability. By contrast, in transition and developing economies, the same mechanisms produce weaker effects because automation is often fragmented, unevenly distributed across sectors, and not sufficiently supported by human capital development or mature management systems. Therefore, the variation in results across country groups should be interpreted not as a contradiction of the model, but as evidence that the productivity effect of AI depends on the interaction between technology and the institutional environment in which it is implemented.

Additionally, structural changes in the labor market are also important. The growth in employment in high-tech sectors in advanced countries, to 17.4% compared to 9.3% in transition countries and 5.4% in developing countries, is also accompanied by a decrease in routine employment and an increase in analytical and technical work tasks. This is consistent with the forecast of Chhibber et al. [46] that almost all jobs will be either transformed or created by AI in developed economies by 2030. The findings of Adhikari [47], Bondarenko et al. [48], Khan et al. [49] suggest that there is a potential for increased risk of technological displacement and job losses. The relatively high share of routine employment in developing countries and the slow pace of people's transition to cognitively intensive professional work further indicate the inability of education and training systems to respond quickly to changing demands, which is an important challenge for human resource management and workforce planning.

The results of accounting and control automation are clearly divided across economic groups. In 2024, 74% of enterprises in advanced countries, 51% in transition countries, and 29% in developing countries implemented AI and integrated it into accounting, auditing, and management control processes. This is consistent with data from Rawashdeh [26], Obaydin et al. [27], and Hammad [28], which showed that AI in the financial and accounting system can improve transparency, internal control, and reduce the risk of management errors. In contrast to these analyses, the results above reinforce current findings and suggest that control improvements only affect economies that have some level of digital capability and automation that is embedded in the overall human resource management framework.

The uneven impact of AI on the labor market and productivity is also confirmed in terms of socio-economic differentiation. These data on the concentration of spending on AI ($118 billion in advanced countries versus $22 and $12 billion in transition and developing countries) reinforce Houenou's [50] observations on the growing disparities in wages and access to high-tech jobs. Ibrahim and Ali [51] interpret the substitution of technological work as a relatively slow process, while in the empirical data (13% decrease in routine occupations, 7% and 5% increase in analytical and technical jobs, respectively), the redistribution of work functions is the most intense. This is consistent with the results of Rahayu et al. [52] that AI is not only changing jobs but also radically changing the nature of work, especially in industries where work is highly automated, deeply integrated with business processes.

An important aspect of the discussion concerns the presence of mixed and partly unexpected results. First, less developed economies demonstrate higher relative growth rates, but these gains occur from a substantially lower productivity base and therefore do not indicate that AI produces stronger absolute effects in those contexts. This pattern reflects a catch-up dynamic rather than a reversal of technological asymmetry. Second, the stability of the share of creative occupations across all country groups suggests that AI-driven labor-market restructuring is not equally pronounced in all occupational segments. In the current phase of digital transformation, the strongest effects are concentrated in routine, analytical, and technical work, whereas creative functions remain comparatively resistant to differentiation at the macro level. Third, transition economies occupy an intermediate position in almost all indicators, but this does not automatically translate into proportional productivity gains. This result may be interpreted as evidence of partial adaptation, in which digital technologies are already present but are not yet fully embedded in organizational routines, managerial systems, and human-capital development strategies. These observations indicate that the proposed approach yields the most explanatory value when AI adoption is systemic and institutionally supported, and less explanatory power when digital transformation remains incomplete, fragmented, or poorly coordinated.

The wider macroeconomic consequences of unequal AI adoption are an especially pertinent part of this conversation. The significant performance of the innovation activity index (0.88 vs. 0.64 and 0.46) and the digital integration index (0.85 vs. 0.66 and 0.52) in advanced countries confirms that AI is becoming an important component of the innovation model of economic growth. These findings are consistent with Wang et al. [53], who demonstrated that AI can optimize industrial structure, improve

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productivity, and reallocate labor across many types of sectors. Similarly, Csaszar and Steinberger [54] suggest that organizations that implement some principles of algorithmic management work like AI – combining knowledge, analysis, and decision-making aspects into a single cognitive model. Given the current conditions, there is a tendency for the effectiveness of AI implementation to be determined not only by attracting investments in technology but also by organizational capacity, accumulation of human capital, and the ability of accounting and control systems to become analytical tools for strategic management.

The focus of the research is limited to the period 2018-2024 and the accumulation of data by country group, which makes it difficult to take into account the long-term effects of AI, regional specificities of regulatory regimes and labor markets. Future studies should examine the long-term effects of AI adaptation on labor markets, institutional policies and inequality dynamics. A desirable option is to model the impact of AI on the quality of human capital, the productivity of management processes and the control system in different sectors of the economy.

6. CONCLUSIONS

The research found that the introduction of artificial intelligence has a positive impact on labor productivity: a 1% increase in automation is associated with a 0.44% increase in productivity, and a 0.31% increase in human capital investment. The average GDP per person employed in 2024 was \$133.2 thousand for advanced countries, \$57.3 thousand for countries with economies in transition, and \$34.0 thousand for developing countries, while in the period from 2018 to 2024, the least developed economies experienced growth of +17.6 to 18.0%, indicating a slow convergence of the three technologies. Industrial productivity and the effectiveness of AI depend on the degree of digital maturity, which was determined by an index of 0.85 for advanced, 0.66 for transition and 0.52 for developing countries. Similarly, the innovation activity index was 0.88, 0.64 and 0.46, respectively. In 2024, the level of automation of accounting and control varied from 74% in advanced economies to 29% in developing countries, and the share of employment in high-tech industries – from 17.4% to 5.4%. These data illustrate that while AI leads to increased productivity and efficiency, it also exacerbates disparities in innovation potential across the world.

The significance of the study lies in showing that the productivity effects of AI are determined not by automation alone, but by its interaction with human capital, innovation capacity, and the level of digital maturity. The study expands current understanding of the links between artificial intelligence, labor productivity, employment restructuring, and the modernization of accounting and control systems. From a practical perspective, the findings may be used to support digital transformation strategies in the areas of labor market adaptation, human resource development, innovation policy, and the improvement of accounting and management control practices.

At the same time, the study has certain limitations. It covers the period 2018–2024 and relies on grouped cross-country data, which does not fully capture long-term effects, sectoral differences, intra-country variation, or the influence of specific national institutional and regulatory environments.

Future research should therefore focus on the long-term socio-economic effects of AI, sector-specific patterns of automation, and the role of institutional conditions in shaping productivity outcomes. It would also be advisable to develop more differentiated models that take into account the quality of human capital and the level of integration of AI into management, accounting, and control systems.

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