

The Impact of Artificial Intelligence and Automation on Labor Markets: The Role of Organizations in Advanced and Developing Economies

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Abstract

This study discusses the role of institutional factors in the effects of artificial intelligence and automation on labor market inequalities. A panel data set covering the period 2005–2024 was used, comprising 7 developed countries (South Korea, Japan, Germany, the United States, France, Italy, and Spain) and 6 developing countries (China, Turkey, Poland, Hungary, Mexico and Brazil). The findings indicate that technological transformation and the spread of artificial intelligence and automation have increased wage inequality in the labor market, though this effect varies across countries. The empirical strategy, tested using fixed-effects panel regression and interaction models, examines three main hypotheses: (H1) AI and automation increase wage inequality; (H2) This effect is more pronounced in developed countries; (H3) Institutional quality significantly moderates this relationship.

The interaction model ($\beta_3 = 0.89$, $p < 0.001$) showed that institutional quality significantly mitigated the effects of technological transformation on inequality. Industrial robotization has significantly increased inequality in advanced economies. In contrast, this effect was less pronounced in developing economies. The results suggest that inequality is shaped not only by technological progress but also by institutional factors.

Keywords

Artificial intelligence (AI), industrial robots, automation, labor market inequality, institutional factors, panel data analysis

Introduction

Artificial intelligence (AI) is widely recognized as a major technological transformation that is reshaping not only the changes occurring in production processes within modern economic systems but also labor markets. While past technological advancements typically led to changes in the nature of manual and routine tasks, artificial intelligence has brought about fundamental shifts in labor demand by encompassing not only manual and routine tasks but also cognitive and productive work, thereby expanding its scope of application (Autor, 2015; Brynjolfsson & McAfee, 2014). This change and transformation have become the subject of intense debate not only because of its significant impact on employment levels, but also due to its effects on the demand for skilled labor, wage levels, social income inequality, and economic imbalances.

The current literature addresses the effects of technological advancements on the labor market primarily through a task-based approach. According to this approach, technological advancements do not eliminate existing occupations but merely lead to changes in their structure and components. In particular, AI-based technologies are replacing human labor in routine and manually codifiable job sectors. However, it has been demonstrated that these technologies actually increase the demand for labor in cognitive and interaction-based job sectors (Autor, Lev, & Murnane, 2003).

However, it has been demonstrated that the effects of AI technology on the labor market and employment levels vary. While some academic studies suggest that technological advancements have led to a decline in labor

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demand, others have shown that technological progress has resulted in increased productivity and higher levels of output (Acemoglu & Restrepo, 2022). The emergence of diverse findings in this context demonstrates that automation and AI-based technological advancements operate through distinct mechanisms. Consequently, it is emphasized that the impact of technological advancement on occupations must be considered in conjunction with its effects on transformation and productivity.

The existing literature is limited and inadequate in two respects. First, a significant portion of the academic studies conducted approach technological developments from a task-oriented perspective (Frey & Osborne, 2017). Consequently, these studies do not adequately explain how organizations are affected by the process of technological transformation. Second, the reasons why the effects of technological developments on the labor market vary from country to country have not been sufficiently examined.

This study addresses the aforementioned gaps in the literature by analyzing the effects of AI-based technological advancements on the labor market through a task-based approach, taking institutional factors into account. The primary objective of the study is to examine the effects of AI technology on employment polarization and income inequality and to analyze these effects within a framework that includes institutional factors. This approach makes it possible to examine how technological transformation is shaped by both task-structural distribution and the institutional context.

In this context, the following hypotheses are being tested:

H1: The spread of artificial intelligence and automation increases wage inequality in the labor market.

H2: The effect of artificial intelligence and automation on wage inequality is more pronounced in high-income (developed) countries.

H3: Firm quality significantly moderates the effect of artificial intelligence and automation on labor market inequalities.

Literature Review

Artificial Intelligence and Its Impact on the Labor Market

In recent years, the impact of artificial intelligence and technological advancements on the labor market has been the subject of intensive research by economic policymakers and social policy circles. Findings from existing studies indicate that technological progress affects labor markets in

various ways. For example, Acemoğlu and Restrepo (2020) have demonstrated that robots, which are extensively used in labor markets, have a downward negative effect on the labor market and wages. In contrast, Brynjolfsson, Rock, and Syverson (2017) emphasize that AI-driven technological advancements, combined with the widespread use of automation and robots in the workforce, will lead to increased productivity and make the impact on employment more complex. In this context, it has become evident that this technological progress yields different outcomes not only across sectors, industries, and occupations but also among skill groups (Autor, 2015). Furthermore, the advancement of digital technologies has expanded this scope to include not only physical production processes but also increases in cognitive productivity and efficiency.

Current research is developing approaches aimed at measuring the effects of artificial intelligence on labor markets in a more scientific and direct manner (Felten, Raj, & Seamans, 2021; Şener, 2024). They have developed an index showing the extent to which occupations are affected by artificial intelligence and have noted that technological advancements vary depending on the nature of the tasks involved. Similarly, Eloundou et. al., (2024), demonstrate that generative artificial intelligence technologies have a more significant impact on cognitive occupations and tasks in particular.

Task-Based Approach and Labor Market Dynamics

It examines the impact of technological progress on labor markets using a task-based approach Autor, Levy, & Murnane (2003). This situation demonstrates that professions are formed by the combination of distinct tasks and skills, and that technological progress leads to changes and transformations in these tasks and skills, depending on the extent to which they benefit from such progress. In this context, while routine and rule-based tasks and processes can be replaced by AI-based automation, it is noted that AI plays a complementary role in professions and tasks that require cognitive skills, problem-solving, and interpersonal communication (Dauth et.al., 2021).

Recent studies indicate that sectors reliant on coding will be replaced by AI-driven technological advancements, alongside more routine and manual tasks, while in skilled sectors based on cognitive skills and interpersonal communication and interaction, these technological advancements will serve as a complementary element. As a result, while technological progress is expected to replace unskilled jobs, it is also anticipated to play a leading role in creating new employment opportunities by enhancing the productivity of the skilled workforce (Autor & Salomons,

2018; Japarova & Shener, 2021). Consequently, it is anticipated that advancements in AI-based technology will have complex effects and give rise to nonlinear, new, and multidimensional employment opportunities.

Artificial Intelligence, Polarization, and Inequality

One of the most significant impacts of the rapid technological advancements of recent years is that these advancements have served as an alternative to the supply of low-skilled labor, thereby excluding this segment from the labor market. Consequently, one of the most significant challenges posed by technological progress is its negative impact on labor markets Autor, Lev & Murnane, (2003) occupations arising from different tasks and their combinations have undergone structural changes alongside technological transformation. As a result, the growing demand for a skilled and educated workforce, rather than an unskilled one, is leading to polarization in employment and, consequently, income inequality (Kaufmann, Kraay & Mastruzzi, 2010).

Studies have shown that technological progress and the increasing use of artificial intelligence are accelerating the deterioration of income inequality and social polarization (Aghion, Antonin, & Bunel, 2019). While artificial intelligence is expected to have a positive impact on innovation and economic growth, it will also lead to a widening gap in wage inequalities based on workers' skills and abilities. Furthermore Korinek & Stiglitz (2017), demonstrate that a significant portion of the effects of artificial intelligence and technological advancements on income distribution is determined by policy and institutional structures.

Organizational Factors

The existing literature indicates that artificial intelligence, alongside new technologies, has profoundly reshaped labor markets. In this context, it suggests that these developments will lead to transformations in the roles within labor markets. Differences in levels of development among countries indicate that they will be affected by these impacts in different ways and to varying degrees. Economic, political, and social differences also lead to varying outcomes. However, analyses conducted at the systemic and institutional levels remain limited. Although many structures—from education systems to employment opportunities—are deeply affected by these changes, these issues have not been sufficiently addressed, particularly at the institutional level. Empirical evidence regarding how technological advancements shape the outcomes of

distributional transformations has not been sufficiently established (Zhang et.al., 2024).

This situation highlights that the effects of technological advancements on labor markets have not been addressed within a comprehensive framework that takes into account their institutional dimensions. While recent academic studies and technological developments have shed light on the functionality of these mechanisms, they have not sufficiently explained how these mechanisms operate or the systematic roles they play.

Data and Methodology

Dataset

This study focuses on the effects of artificial intelligence tools—which are rapidly becoming widespread as a result of technological advancements—on labor markets. The study is based on country-level panel data covering the period from 2005 to 2024. This period represents a time when technological advancements led to a significant increase in automation and the widespread use of robots in the workforce. (Acemoglu & Restrepo, 2020).

The datasets are structured as a balanced panel comprising OECD member countries and certain emerging economies. Consequently, they have been included in the analysis due to differences in economic development and institutional frameworks across countries. Thus, this study examines how the effects of artificial intelligence on the labor market manifest due to variations in economic conditions and institutional structures. The literature emphasizes that technological developments vary depending on institutional frameworks and that, consequently, the results of comparative analyses are more robust. In this context, it is crucial to include data sets from both developed and developing economies to test the study's institutional moderation hypothesis.

The data used in this study were drawn from the World Development Indicators (WDI) and International Labour Organization (ILO) datasets provided by the World Bank. Data on artificial intelligence applications and the use of industrial robots were obtained from the International Federation of Robotics. Additionally, data on the use of digital technologies and artificial intelligence were utilized to obtain more comprehensive information. These data were analyzed, particularly by the OECD, not only to assess automation and artificial intelligence but also their cognitive impacts. Furthermore, the World Governance Indicators datasets were included to measure dimensions such as the rule of law, legal regulations, forms of

government, and levels of democracy and corruption in countries.

The combined use of all these datasets provides this study with a significant opportunity to analyze how technological progress—particularly automation and digitalization—shapes the multidimensional effects on labor markets within an organizational context. Consequently, these datasets provide the necessary temporal and cross-sectional variation required to test the hypotheses.

Variables

The variables used in this study are classified as dependent, independent, moderator, and control variables for the purpose of analyzing the effects of artificial intelligence on the labor force. All variables and data sources are presented in Table 1. Two primary dependent variables were used to analyze labor market outcomes. The first measures polarization in labor markets through the share of mid-skill jobs in total employment. This approach is based on a task-based analysis of the changes in employment brought about by technological progress (Goos, Manning, & Salomons, 2014; Autor, 2015). The second is based on the Gini coefficient, which measures income distribution and wage inequality. In this context, it is emphasized that empirical studies examining the relationship between technological developments and income distribution are consistent with this view (Piketty, 2014).

Industrial robot density, which refers to the number of robots per worker, is used to measure the level of artificial intelligence and robot technology employed in the workforce. This variable is widely accepted as a standard metric for assessing the impact of automation on employment (Graetz & Michaels, 2018). It is based on data from the World Governance Indicators, which represent and reflect institutional quality, and encompasses government effectiveness, the rule of law, and legal and regulatory frameworks. It also includes variables such as per capita income, education levels, and business transparency. It is designed to track macroeconomic factors that could influence labor markets and alter their outcomes (OECD, 2019).

Table 1: Variable Definitions

Variable	Definition	Measurement	Source
Polarization	Share of jobs requiring medium-level skills in total	Share of medium-skill occupations in total employment according to the	ILO/World Bank

	employment	ISCO classification	
Inequality	Gini coefficient	Gini coefficient	World Bank
AI/Automation	Robot density	Number of robots per 10,000 workers	IFR
Corporate Quality	WGI index	Average of WGI sub-components	World Bank
GDP	Level of economic development	GDP per capita at constant prices	World Bank
Education	Human capital index	Average years of education/higher education rate	World Bank
Commercial transparency	Trade/GDP	(Exports + Imports) / GDP	World Bank

Table 1 summarizes the definitions and measurement methods of the variables used in the study. Accordingly, the dependent variables were defined using indicators of polarization and income inequality to reflect structural transformations in the labor market. Robot density is a widely used indicator in the literature to measure the level of automation. It thus provides the opportunity to analyze the effects of technological developments on labor demand (Graetz & Michaels, 2018). Additionally, the institutional quality variable was included in the model to test its effect; this variable allows us to examine how the impact of artificial intelligence technology on labor markets may vary within an institutional context (Aghion et al., 2022). The control variables, on the other hand, aim to enhance the reliability of the estimation results by isolating the effects of factors such as economic development level, human capital, and openness to the outside world.

Econometric Model

The panel data approach is used to obtain more reliable and consistent estimates by controlling for unobservable heterogeneity arising from cross-country economic and sociological differences (Wooldridge, 2010; Hsiao, 2014). In this study, a fixed-effects model within a panel data framework was used to analyze the impact of artificial intelligence technology on labor markets. In this context, the study’s basic empirical model is defined as follows:

$$Y_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Inst_{it} + \beta_3 (AI_{it} \times Inst_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

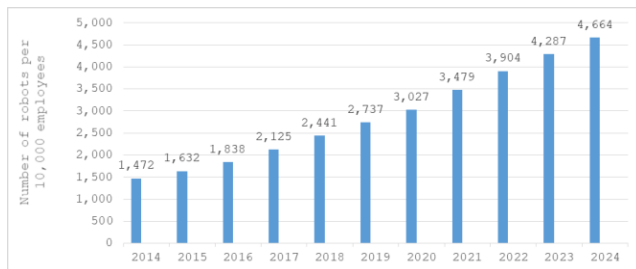
In this equation Y_{it} country i 'in time t ' represents the labor market outcome observed (polarization or income inequality). AI_{it} AI and level of automation, $Inst_{it}$ while representing corporate quality X_{it} represents the control variable. μ_i Country-specific fixed effects λ_t represents the shocks over time. This model is consistent with the fundamental assumptions of the study. Focusing on Hypothesis H1 and Hypothesis H2, The β_1 value examines the outcomes of AI-driven workforce initiatives. Similarly, the β_3 value, which determines the testing of H3 indicates whether institutions are strong or weak and how this is demonstrated. Consequently, this demonstrates that the emergence of the interaction in question aligns with studies showing that technological transformation varies by context, as highlighted by (Acemoglu & Restrepo, 2020) or noted by (Aghion et. al., 2022).

The fixed-effects estimation method assumes that the culture and institutions of specific countries do not change over time. Consequently, it reduces estimation bias by controlling for structural conditions that remain constant over many years. This method allows for the inclusion of economic and technological shocks that affect all countries simultaneously. As a result, this approach is considered a standard model in panel data analysis (Wooldridge, 2010).

However, various measures have been incorporated into the model to reduce statistical errors. First, standard error methods are applied in cases where the distribution is not normal or serial correlation is present. Second, taking into account the potential endogeneity issue of the AI variable, alternative model specifications were estimated using lagged independent variables. As a result, similar methods are recommended in the literature to clearly establish the causal relationship (Acemoglu, Autor & Jhonson, 2026). Finally, robustness analyses are conducted to redefine and validate the variables, thereby enhancing the reliability of the results. The purpose of these analyses is to demonstrate that the results are not dependent on specific assumptions.

Findings

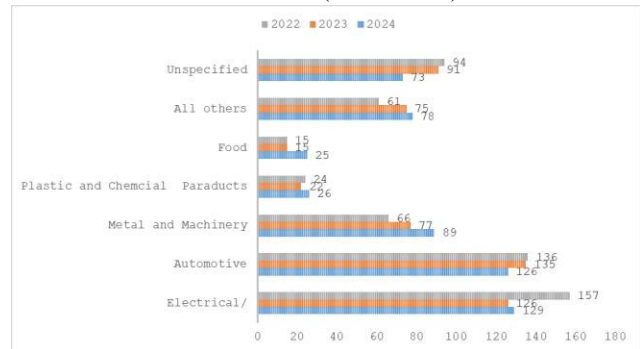
Figure 1. Growth of the Global Industrial Robot Fleet (2014–2024)



Source: World Robotics 2025

As shown in Figure 1, the annual trend in robot density per 10,000 people globally between 2014 and 2024 is illustrated. In particular, it has been observed that robot density in the industrial sector has increased rapidly in recent years, in tandem with rapid technological advancements. Technological advancements have led to a rapid increase in demand for AI-based robots aimed at improving labor productivity. While the use of robots in the workforce was more limited prior to 2010, this rate showed a significant increase after 2015 and has risen to significant levels in many countries since 2020. Overall, the proportion of robots in the workforce is steadily increasing, and technological competition among countries is driving the adoption of robotics.

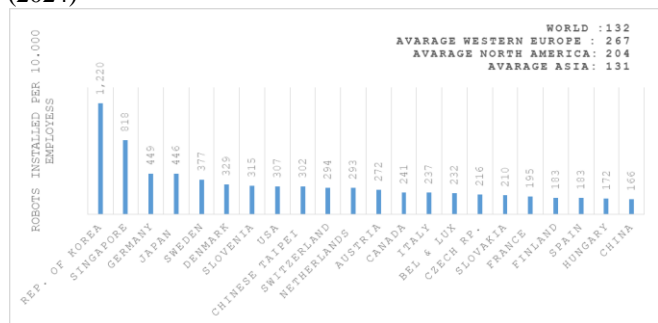
Figure 2. Sectoral Distribution of Industrial Robot Installations in Recent Years (2022–2024)



Source: World Robotics 2025

Figure 2 shows the distribution of industrial robot installations across sectors in recent years. According to data from the International Federation of Robotics, robot technology is concentrated in certain sectors but exhibits a heterogeneous distribution at the sectoral level. Rather than illustrating a temporal trend, this graph provides a complementary perspective on the sectoral structure of robot technology.

Figure 3. Robot Density in the Manufacturing Industry (2024)



Source: International Federation of Robotics

Both developed and developing economies have begun to make extensive use of AI-based robots to increase efficiency in economic activities. In particular, the integration of robots into factory systems in the manufacturing sector has marked a new phase in the production chain. The use of robots in the manufacturing sector reached record levels in 2024. In Western Europe, the ratio stood at 267 per 10,000 workers, while in North America it was 204 and in Asia it reached 131 (Robotics, 2026).

While robot density grew by approximately 3% in Western Europe (Germany, Switzerland, the Netherlands, Spain, Austria, Italy, Belgium, and France), in North America (the U.S., Canada, and Mexico), this rate stood at 4%, and the largest increase occurred in Southeast Asia (South Korea, Singapore, Japan, and Taiwan) with an 11% rise. According to China National Bureau of Statistics data, the People’s Republic of China (PRC) recorded a record-breaking 17% growth. While the PRC maintains its leading position in global industrial robot usage, Japan ranks second. In 2024, more than half—54% (295,000)—of global industrial robot installations were deployed in China. However, with a robot density of 10,000 per worker, the Republic of Korea has the highest robot usage. It has been growing at an annual rate of 7% since 2019. Singapore ranks second with 818 units, while Germany ranks third with 449 units (Robotics, 2026).

Baseline Regression Results

The findings presented in this section highlight key trends regarding global robot density in industries based on artificial intelligence and automation. According to these findings, robot density is steadily increasing on a global scale, and the use of robots in production processes is rapidly becoming widespread. According to data from the International Federation of Robotics, technological transformation is becoming a continuous process in line with the increase in the robot stock, and it is evident that robots are playing a more active role in production processes (Cobin & Hobijn, 2010).

However, on a sectoral basis, technological density follows a heterogeneous trajectory and is concentrated in specific industrial sectors. Consequently, technological transformation does not follow a homogeneous trajectory across sectors, and the manufacturing sector, in particular, plays a dominant role. Therefore, the varying levels of technological intensity across sectors also reveal that technological advancements have differing impacts on job roles (Autor, Levy, & Murnane, 2003). At the country level, alongside differences in technological progress, the use of automation and AI-based technological robots in the

workforce also varies. This variation is attributed to the close relationship between the adoption of technological transformation and the levels of integration within countries’ economic and institutional structures (Acemoglu & Restrepo, 2020).

When analyzed broadly, it is evident that there is a heterogeneous structure and distribution in terms of location and time due to countries’ economic infrastructure and cultural adoption of technology. Consequently, it is evident that technological progress has given rise to a multidimensional system of automation and artificial intelligence. Therefore, it is stated that this leads to differences in the distribution of tasks and responsibilities depending on the specific conditions of each country. Consequently, the next section presents econometric findings to facilitate a systematic analysis of these relationships.

The Role of Organizational Factors (Interaction Effects)

This section analyzes how the effects of artificial intelligence and automation technologies on labor markets are shaped by institutional structures. To this end, the basic model presented in the previous section has been expanded by adding an interaction term between robot density and institutional quality indicators. This allows us to test how the effects of automation respond to a country’s institutional characteristics. Additionally, indices reflecting a country’s governance quality and institutional effectiveness have been used as institutional quality indicators. These variables are considered key factors shaping the effects of technological transformation, alongside factors such as labor market regulations, education systems, and social protection mechanisms.

Model: $RD_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Inst_{it} + \beta_3 (AI_{it} \times Inst_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$

Table 1. The Role of Organizational Factors: Results of the Interaction Model (AIit × Instit)

Variable	Coefficient (β)	Standard Error	t - value	p-value
Constant (β0)	19.34	8.21	2.36	0.019
AIit (Year)	1.42	0.11	12.91	p <0.001
Instit (Developed=1)	45.67	15.33	2.98	0.003
AIit × Instit	0.89	0.21	4.24	p <0.001

Note: N=280 (13 countries, 2005–2024). Developed: South Korea, Japan, Germany, the United States, France, Italy,

Spain. Developing: China, Turkey, Poland, Hungary, Mexico, Brazil. Fixed effects (country + year) have been controlled for.

Table 1 presents the findings related to the interaction model. According to the analysis results, the coefficient for the interaction term ($AI_{it} \times Instit$) is positive and statistically significant ($\beta = 0.89$, $p < 0.001$). This finding indicates that the effect of institutional factors on robotization is not direct but is shaped through an interaction with technological progress. In other words, the contribution of the distribution of artificial intelligence and automation (AI_{it}) to robot density is significantly higher in institutionally developed countries compared to developing countries. This suggests that institutional factors play a supportive role in the automation process.

Control Variable and Economic Interpretation

Findings regarding the control variables added to the model to accurately identify the effects of technological transformation on the labor market yield meaningful results consistent with economic theories. First, there is a positive relationship between per capita income and income inequality. The substitution of technology leads to a deepening of wage inequality based on individuals' skills and abilities. According to the April 2026 World Robotics 2025 report by the International Federation of Robotics (IFR), South Korea ranks first globally among the developed countries in our panel with a robot density of 1,220. Following South Korea, Germany (449), Japan (446), and the United States (307) rank as the countries with the highest robot densities (Automation, 2026; ITmedia, 2026). In these countries, the trend of income inequality is more pronounced in parallel with the high robot density. In contrast, among developing countries, China has a robot density of 166 due to its large population, despite having approximately 2 million operational robots. Globally, approximately 55% of robots installed in 2024 (295,000 units) were installed in China (Automation, 2026). Furthermore, according to the World Bank's World Development Indicators (WDI) report released in July 2025, per capita income in China and other developing countries has increased demand for skilled labor, thereby widening the gap in wages (World Bank, 2025). Second, the mitigating effect of educational attainment on income inequality. This demonstrates that a skilled workforce can adapt quickly to technological transformation. According to the World Bank Policy Research Report (2024), digitalization has led to increased demand for a skilled workforce in developing economies, and thus support for investments in education can help reduce income inequality.

For example, while the impact of automation on deepening inequality is limited in countries with strong education systems such as Germany and France, it has been shown that higher levels of automation in Poland and Hungary have further deepened income inequality (World Bank, 2025).

Third, the limited but significant effect of the trade openness variable. Rapid technological advancements worldwide are leading to changes in labor market dynamics. In their study of 52 countries, Ribeiro and Prettnner (2025) found that trade integration can exacerbate the inequalities caused by automation, but that this effect varies significantly depending on a country's level of development. In this context, they noted that this holds true for countries like China, Hungary, and Mexico, which are based on export-oriented industrialization. Therefore, when all these findings are evaluated together, they indicate that institutional factors and investments in human capital play a supportive role in mitigating the negative effects of technological transformation.

Robustness Checks

In the study, comprehensive robustness analyses were conducted to test the reliability of the findings and the sensitivity of the model metrics. First, the model was re-estimated using alternative measures of the dependent variable (robot density). According to the IFR's World Robotics 2025 report, robot density (number of robots per 10,000 people) has been appropriately adjusted for the 13 countries and 20 years of data in our panel. According to the IFR (2026) report, while there are 132 robots per 10,000 workers globally, this figure averages 267 in Western Europe, 204 in North America, and 131 in Asia (European Central Station, 2026).

Second, to control for the reverse causality problem, lagged values of the artificial intelligence and automation variables (lagged by 1, 2, and 3 years) were included in the model. A similar method was used in the study by Ribeiro and Prettnner (2025), which demonstrated that lagged models play a critical role in capturing the causal effects of automation on inequality (Ribeiro & Prettnner, 2025). In this context, the coefficients of the lagged variables are consistent with the main model and support the direction of causality from technology to the labor market.

Third, different projections have been made for different groups of countries. The primary basis for this distinction is the classification of developed countries (South Korea, Japan, Germany, the United States, France, Italy and Spain) and developing countries (China, Turkey, Poland, Hungary, Mexico and Brazil). A study by Ribeiro and Prettnner (2025)

similarly found that the effect of robots on increasing income inequality is more pronounced in developed countries and relatively less pronounced in middle- and lower-middle-income countries.

Finally, the model was re-estimated after excluding Chinese data to account for various observation effects. China's robot density per worker in 2024 (166) was above the global average (132), and its total operational robot stock (2,000,000 units) and annual installations (295,000 units) ranked first in the world (European Central Station, 2026). The panel clearly shows China in the lead.

In conclusion, the results of all these robustness tests indicate that our key findings are not sensitive to the variable definitions of the model tools or the country sample. Therefore, our results regarding the effects of artificial intelligence and industrial robots on the labor market are shown to be consistent both qualitatively and quantitatively under different specifications.

Conclusions and Policy Recommendations

This study covers 13 countries for the period 2005–2024 (Advanced economies: South Korea, Japan, Germany, the United States, France, Italy, Spain; Emerging economies: China, Turkey, Poland, Hungary, Mexico, Brazil). Our empirical strategy is based on an interaction model constructed within the framework of fixed-effects regression. In this context, the key findings are supported by robustness analyses.

The analysis results indicate that the rapid spread of employment driven by technological advancements, as well as the effects of artificial intelligence and automation systems on labor market inequalities, are neither linear nor uniform. They reveal that these dynamics are shaped by complex interactions influenced by a country's economic infrastructure, ability to adapt to technological developments, level of equality, trade openness, and constitutional systems. A key finding of our interaction model—the positive and significant $AIit \times Instit$ coefficient ($\beta_3 = 0.89$, $p < 0.001$)—reveals that in economies with advanced institutional systems, AI-based automation systems and robots tend to exacerbate inequalities in labor markets. In developing countries, however, this effect appears to be relatively less pronounced. This is consistent with the theory of skill-based technological change. While the increasing demand for skilled labor in advanced economies widens the gap in wage differentials, the disruptive impact on labor markets in developing economies remains relatively limited due to the weak technological trend in these economies.

Although institutional factors do not have a direct effect, it has been statistically proven that technological advancements and technological transformation exert a strong influence on labor markets. This finding aligns with the global robot density of an average of 132 robots per 10,000 workers in 2024, according to the World Robotics (2025) report published by the IFR. However, although robot density more than doubled between 2014 and 2024, the positive effects on economic growth have been unevenly distributed due to economic and systemic differences among countries. For example, South Korea ranks first in the world in terms of robot density with 1,220 robots per 10,000 workers, while in Mexico this figure is only 62. Additionally, China, with a robot density of 166, is performing above the global average and holds the world's top position in total operational stock, with approximately two million robots and an annual installation rate of 295,000 units. According to a 2026 World Bank report, the rapid advancement of artificial intelligence and automation, driven by technological progress, is unevenly distributed across countries' levels of development. For example, while internet usage in developed countries exceeded 90% in 2024, this rate remained at only 27% in developing countries. Similarly, the number of people without internet access in least developed and developing economies was recorded at 2.6 billion. This digital divide directly and indirectly leads to similar inequalities in the adoption rates of artificial intelligence and automation. In this context, it once again highlights the importance of institutional factors in developing countries. In this regard, a study conducted by Riberio and Prettnner (2025) across 52 countries revealed that artificial intelligence and industrial robots increase demand for skilled labor, leading to rises in bonuses and wages, and consequently exacerbating wage inequality. However, data analyses conducted in these countries reveal three key findings. First, the substitution effect of automation on low- and medium-skilled employment is relatively stronger in developing economies. A study by Das et al. (2025) found that variables such as internet penetration, innovation capacity, per capita GDP, and the proportion of skilled labor play a significant role in the relationship between automation and AI and their impact on employment. Second, reskilling programs are more common in advanced economies, where they are associated with trade union rights, bargaining power, and similar organizational factors. In their study, Falk and Tsoulakas (2026) noted that in a competitive market, each firm focuses on the effects of its own automation decisions on demand. Consequently, they demonstrate that this results in negative effects on aggregate demand and that externalities are not taken into account. Finally, during the period covered by our study, significant disruptions occurred in global labor

markets. According to the ILO's 2025 World Employment and Social Outlook (WESO) report, the global GDP growth forecast has dropped from 3.2% to 2.8%, and employment projections have fallen from 60 million to 53 million. Consequently, the findings indicate that 100,000 technology workers were laid off in 2025, with more than half of these cases attributed to technological automation (Westover, 2026). In light of these findings, it is noted that traditional policy tools (reskilling, universal basic income, capital taxes, voluntary agreements, etc.) have proven insufficient in mitigating the externalities of AI and technological progress to optimal levels (Das et. al, 2025; Falk & Tsoukalas, 2026). These findings offer important insights for policymakers. First, reducing the inequalities caused by technological transformation is not merely a matter of increasing the number of robots; it also requires improving institutional quality and implementing necessary reforms. For example, policy frameworks for Human-Centered Artificial Intelligence developed by the OECD and ILO should be utilized. Therefore, a comprehensive approach that addresses not only technological transformation but also labor force transformation, social impacts, and ethical criteria must be adopted. Second, the restructuring of education systems plays a crucial role in ensuring that technological transformation progresses in a healthy manner. As our findings also indicate, there is a clear link between educational attainment and the reduction of inequality. For instance, Singapore's 2026 budget includes a significant allocation for free access to premium AI tools for six months. In this context, the government has not only ensured public access to technology but has also implemented serious policies and initiatives to promote the effective use of technology through AI literacy programs. Similarly, China has allocated \$45.2 million to R&D efforts and targeted educational reforms. Third, sustainable policies must be developed with due consideration for the environmental impacts of AI and automation. In this context, at the World Bank's WDR Regional Consultation Meeting in Tokyo in 2025, it was noted that China's water consumption had surpassed that of Denmark and its electricity production had exceeded that of Japan, highlighting the magnitude of environmental challenges. In this context, the roadmap proposes that AI technologies be designed in alignment with international standards for sustainability, energy efficiency, and data security, and that technology policies be structured accordingly. Finally, it calls for the restructuring of social policies to mitigate the effects of social welfare and income inequality. As highlighted in the study, implementing social protection policies such as a Universal Basic Income is crucial to mitigate the disruptive effects of artificial intelligence and automation systems on the incomes of unskilled workers.

However, the first priority is to accelerate the development of digital infrastructure, thereby strengthening the role of the internet and automation in boosting local employment and enhancing their substitution effects. According to World Bank (2025) data, despite access to electricity in some developing South Asian countries, internet usage rates remain around 60%. Digital reform policies and improvements to technological infrastructure will pave the way for supportive effects to emerge, rather than automation displacing employment. Second, new systems must be developed to integrate automation-based professions with technological advancements. Technological transformation must be monitored through early intervention systems in collaboration with organizations to ensure a balanced process of change and transformation. Finally, it is essential to systematize organizational impact assessments for AI. According to OECD (2025) data, globally, 91.6% of companies use AI in a superficial and regulatory framework, while only 28.7% report using AI in production and transformation processes.

In conclusion, this study demonstrates that the effects of artificial intelligence and automation on labor markets are not uniform. Consequently, it highlights that these effects can be shaped and directed through institutional factors and investments in human capital. Alongside technological transformation, strong institutions, inclusive education systems, and technological advancements must be advanced in a human-centered and inclusive, sustainable direction.

Declarations and Statements

Ethical Considerations

This study does not require ethics committee approval. No human or animal subjects were involved, and no surveys, interviews, or observational methods requiring ethics approval were conducted.

Participant Consent

No participants were involved in this study; therefore, informed consent was not required.

Consent for Publication

This manuscript does not contain any individual data, images, or videos. Hence, consent for publication is not applicable.

Conflict of Interest Statement

The author(s) declare that there are no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Data Availability

No datasets were generated or analyzed during the current study. Therefore, data availability is not applicable.

Declaration of AI Usage

Artificial intelligence tools were employed solely for language support, grammar correction, and formatting adjustments in this manuscript. The academic content, interpretations, and conclusions are entirely the responsibility of the author(s).

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