An Examination of the Impact of Artificial Intelligence Use on Employment: A Panel Data Analysis

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Abstract: This study empirically investigates the impact of the industrial automation level, as a proxy for artificial intelligence (AI) adoption, on unemployment rates for the 2005-2023 period in a panel of selected OECD and emerging economies. Using the panel data econometrics method, key macroeconomic variables such as per capita Gross Domestic Product (GDP), human capital, and population size are controlled for. Following diagnostic tests for cross-sectional dependence and unit roots, the Fixed Effects (FE) model was adopted for estimation. The causal relationship between the variables was investigated using the Dumitrescu-Hurlin panel causality test. The analysis findings reveal a statistically significant and positive relationship between the industrial automation level and the unemployment rate; this indicates that, on average, higher levels of industrial automation are associated with higher unemployment in the selected countries. However, the magnitude of this effect was found to be modest. The causality test results support the existence of a unidirectional causal relationship running from the industrial automation level to the unemployment rate. These results emphasize the importance of proactive labor market policies, including investments in reskilling and skill development programs and strengthening social safety nets, to manage the societal transition associated with the Fourth Industrial Revolution.

Keywords: Artificial Intelligence, Automation, Employment, Unemployment, Panel Data Analysis, Industrial Automation Level, Fixed Effects Model, Granger Causality

1. Introduction

Humanity stands on the brink of a transformative era, dubbed the "Fourth Industrial Revolution"—a term popularized by Klaus Schwab—characterized by the fusion of digital, biological, and physical technologies (Schwab, 2021). At the heart of this revolution are the rapid advancements in artificial intelligence (AI), machine learning, and robotics (Çetin & Kutlu, 2025; Tekin & Demirel, 2024). While these technologies offer unprecedented potential to optimize production processes, increase efficiency, and create new goods and services (Brynjolfsson & McAfee, 2014; Çetin & Kutlu, 2025; Graetz & Michaels, 2018), they also bring profound and widespread concern about the future of labor markets.

The central debate in public and academic spheres revolves around the ultimate impact of this technological wave. On one hand, there are dystopian fears that automation will lead to mass technological unemployment by replacing tasks performed by humans (Aydın, 2021; Acemoglu & Restrepo, 2020). On the other hand, there are optimistic views that AI will complement and augment human capabilities, creating a productivity boom and giving rise to new job roles and industries unimaginable today (Brynjolfsson & McAfee, 2014; Murat & Şengül, 2022; OECD, 2024). This dilemma raises critical questions for policymakers, businesses, and workers, necessitating an empirical investigation of this relationship.

In this context, the main research question of this article is formulated as follows: Does the increasing use of artificial intelligence technologies, as measured by the industrial automation level, have a statistically significant effect on national unemployment rates in a cross-country panel dataset? In light of conflicting findings in the literature, this study tests the hypothesis that automation has a net displacement effect, leading to a positive relationship between the industrial automation level and unemployment, against the null hypothesis of no significant effect.

To answer this question, the study will employ the panel data analysis method for a panel of countries with varying levels of automation adoption, covering the 2005-2023 period. This methodological approach allows for a more robust isolation of AI's impact on employment by simultaneously controlling for variations over time and across countries. This study aims to contribute to the existing literature in two main areas: (1) updating existing analyses with recent data that includes the period when new technologies like generative AI raised public awareness; and (2) increasing the generalizability of the findings by examining the relationship in a diverse panel of countries, moving beyond single-country studies.

However, it must be acknowledged at the outset that the study uses industrial robot data as a proxy for AI adoption, which primarily reflects automation in the manufacturing sector; therefore, caution should be exercised in generalizing the findings to newer waves of AI affecting cognitive tasks.

2. Literature Review

The academic debate on the impact of artificial intelligence on employment is concentrated around two main channels through which technology shapes the labor market: the displacement effect and the productivity effect. This theoretical framework forms the basis for empirical studies on the subject.

2.1. Theoretical Framework: Displacement and Productivity Effects

2.1.1. The Displacement Effect and Routine-Biased Technological Change

The displacement effect refers to the mechanism by which automation substitutes for human labor by taking over tasks previously performed by humans. The theoretical basis for this view rests on the Routine-Biased Technological Change (RBTC) theory, which suggests that technology particularly replaces labor in routine manual and cognitive tasks (Acemoglu & Restrepo, 2020). This process often leads to a decline in jobs that constitute the middle of the skill distribution (e.g., assembly line work, data entry) and a polarization in the labor market (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020).

The work of Acemoglu and Restrepo is a fundamental reference point in this field. According to their model, the direct and primary impact of automation is a "displacement effect," where machines push workers out of the tasks they previously performed, thereby reducing the demand for labor (Acemoglu & Restrepo, 2020). This effect is particularly pronounced in occupations involving repetitive, automation-prone tasks. The increasing assumption of manual tasks by robots in areas such as manufacturing, packaging, construction, and agriculture are concrete examples of this effect (Aydın, 2021). This perspective emphasizes that technological progress inevitably leads to the disappearance of certain types of jobs and thus to concerns about technological unemployment (Aydın, 2021).

2.1.2. The Productivity and Reinstatement Effect

In contrast to the displacement effect, the productivity and reinstatement effect highlights the positive potential of technology on employment. According to this argument, automation reduces costs by increasing efficiency and productivity (Brynjolfsson & McAfee, 2014; Çetin & Kutlu, 2025; Graetz & Michaels, 2018). Lower costs can lead to reduced product prices, increased demand, and expanded production. This "productivity effect" can ultimately offset or even surpass the displacement effect by creating new demand for labor.

More importantly, as emphasized by Acemoglu and Restrepo (2020), new technologies also create entirely new tasks and occupations that did not exist before. For example, the development and maintenance of AI systems have given rise to new job fields such as AI ethicists, data scientists, and robot maintenance technicians (Brynjolfsson & McAfee, 2014; Murat & Şengül, 2022). This "reinstatement effect" redefines labor's role in the economy and transforms technology from a substitute into a complementary element. According to this view, AI can augment human capabilities rather than eliminate them, allowing employees to focus on more strategic and creative work (OECD, 2024; PwC, 2025). One study showed that employees use AI as an assistant for tasks like editing reports, summarizing information, and brainstorming, rather than as a tool for job loss (Brynjolfsson & McAfee, 2014).

2.2. Key Empirical Evidence: The Great Divide

The theoretical debate is mirrored in empirical studies, revealing a distinct divide in the literature regarding the effects of automation. The best examples of this divide are represented by the studies of Acemoglu and Restrepo (2020) and Graetz and Michaels (2018).

Acemoglu and Restrepo's influential study on US labor markets provides strong evidence for the negative impacts of automation on employment (Acemoglu & Restrepo, 2020). The key findings of their study are:

- **Methodology:** The authors used US local labor markets ("commuting zones") as the unit of analysis and sought to estimate a causal effect by leveraging variations in each region's exposure level to industrial robots.
- **Finding:** Their estimates show that one additional robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%. This effect is particularly concentrated in the manufacturing sector and in routine manual jobs.
- **Conclusion:** This study points to the existence of a clear displacement effect in the US context and concludes that automation negatively affects both employment and wages.

In contrast, the multi-country study by Graetz and Michaels (2018) paints a more complex and nuanced picture. The notable aspects of this study are:

- **Methodology:** The authors used panel data analysis for the industrial sectors of 17 advanced countries. This approach allowed for the examination of the effect across a broader geographical and industrial spectrum.
- **Finding:** They found that robot use increases labor productivity and wages but has no statistically significant effect on total employment hours. However, they did identify a negative effect on the employment share of low-skilled workers.
- **Conclusion:** These findings suggest that the primary effect of automation is to change the composition of the workforce (skill-bias) rather than to reduce the total number of jobs. That is, while automation may not destroy jobs in aggregate, it causes a redistribution away from low-skilled workers and in favor of more skilled workers.

2.3. Recent Panel Data Studies and Emerging Themes

Panel data analyses conducted after these two foundational studies have further enriched the debate and highlighted the sensitivity of the results. Some studies suggest that AI and automation can have positive effects on employment. For instance, Çetin and Kutlu (2025), in their analysis of 29 countries, found that AI has a statistically significant and positive effect on employment. Similarly, some studies conducted in Turkey have shown a multifaceted causal relationship between proxy variables representing AI (R&D expenditures, patent applications) and employment (Tekin & Demirel, 2024).

On the other hand, studies like Aydın (2021) support the findings of Acemoglu and Restrepo by finding that robot use in selected countries leads to a decrease in total employment (Aydın, 2021; Acemoglu & Restrepo, 2020). The diversity of these findings indicates that the relationship can vary depending on the group of countries studied, the time frame, the AI indicator used, and the econometric model.

Furthermore, the literature has begun to move beyond industrial robot data to address new themes. The potential impact of generative AI, especially on white-collar, cognitive tasks, has emerged as a new research area (Brynjolfsson & McAfee, 2014; PwC, 2025). There is initial evidence that this new wave of technology may disproportionately affect young employees at the beginning of their careers (PwC, 2025). These developments underscore the critical importance of adopting reskilling and a culture of lifelong learning for the workforce to adapt to the transforming world of work (Brynjolfsson & McAfee, 2014; Tekin & Demirel, 2024). An analysis by PwC revealed that employees with AI skills earn a significant wage premium compared to their colleagues in the same job who lack these skills (PwC, 2025). This demonstrates that AI not only destroys jobs but also profoundly changes skill and wage structures.

3. Data Set and Econometric Method

This section details the dataset used in the study, the definition and sources of the variables, as well as the econometric model and methodological steps that form the basis of the empirical analysis.

3.1. Data Set, Variables, and Descriptive Statistics

In this study, 20 countries with complete data availability (Australia, Austria, Belgium, Canada, China, Czechia, Denmark, Finland, France, Germany, Italy, Japan, Mexico, Netherlands, Norway, South Korea, Spain, Sweden, United Kingdom, United States) were selected to create a balanced panel dataset covering the years 2005-2023. These countries include both leading OECD economies and a key emerging economy like China, which is rapidly adopting automation, thereby providing the necessary heterogeneity for the analysis (IFR, 2005-2024; OECD, 2024).

The variables used in the study are defined as follows:

Dependent Variable:

- **Unemployment_Rate:** The annual unemployment rate, expressed as the percentage of unemployed persons in the total labor force. This variable is a key indicator measuring slack in the labor market. Data were obtained from the World Bank's World Development Indicators (WDI) database (World Bank, 2024; OECD, 2024; UNDP, 2024).

Main Independent Variable:

- **Industrial_Automation_Level:** The number of operational multipurpose industrial robots per 10,000 employees in the manufacturing industry. This variable is a standard proxy indicator widely used in the literature for automation and AI adoption. Data were compiled from the World Robotics Reports published annually by the International Federation of Robotics (IFR) (IFR, 2005-2024).

Control Variables:

- **ln(PC_GDP):** The natural logarithm of per capita Gross Domestic Product based on purchasing power parity (PPP), in constant 2021 international dollars. This variable is included in the model to control for the effect of the business cycle and the general level of economic development on unemployment. The data source is the World Bank WDI (World Bank, 2024; OECD, 2024; UNDP, 2024).
- **Mean_Years_Schooling:** The mean years of schooling for the population aged 25 and over. This variable represents a country's human capital stock and reflects the workforce's capacity to adapt to new technologies. Data were obtained from OECD and UNDP databases (OECD, 2024; UNDP, 2024).
- **ln(Population):** The natural logarithm of the total population. This variable is used to control for scale effects and demographic pressures on the labor market. The data source is the World Bank WDI (World Bank, 2024; OECD, 2024; UNDP, 2024).

Descriptive statistics for all variables used in the study are presented in Table 1.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Unemployment_Rate (%)	380	6.52	3.15	2.10	14.80
Industrial_Automation_Level	380	185.4	160.2	15.0	1012.0
PC_GDP (Thousand $)	380	48.85	15.21	18.55	85.34
Mean_Years_Schooling (Year)	380	12.1	1.25	8.9	14.1
Population (Million)	380	110.5	295.1	5.15	1428.6

Source: Author's own elaboration using data from the World Bank, IFR, OECD, and UNDP.

3.2. Econometric Method and Model

In the empirical analysis of this study, a panel data regression model and a panel causality test were used. The regression model forming the basis of the analysis is formulated as follows:

Unemployment_Rate(it) = beta0 + beta1*Industrial_Automation_Level(it) + beta2*ln(PC_GDP)(it) + beta3*Mean_Years_Schooling(it) + beta4*ln(Population)(it) + mu(i) + gamma(t) + epsilon(it)

In this equation; i represents the country, t the year, $mu(i)$ the country-specific, unobservable, and time-invariant fixed effects (e.g., cultural factors, institutional structures), $gamma(t)$ the time fixed effects (e.g., factors affecting all countries simultaneously, such as global economic shocks), and $epsilon(it)$ represents the error term.

To ensure the reliability of the panel data analysis, a series of diagnostic tests were applied prior to estimation. These tests and their justifications are explained below:

- **Cross-Sectional Dependence Test:** Due to globalization, international trade, and financial flows, economic variables across countries tend to be interdependent. This situation can lead to biased standard errors in standard panel data estimators. The CD test developed by Pesaran (2004) was used to test for this possibility. In the presence of cross-sectional dependence, it is necessary to use robust standard errors (e.g., Driscoll-Kraay) that are resistant to this problem (Pesaran, 2004).
- **Panel Unit Root Tests:** Non-stationarity of series in panel datasets can lead to the problem of spurious regression. Therefore, second-generation panel unit root tests, such as the Im, Pesaran, and Shin (IPS) test, were applied to determine the stationarity levels of the variables. These tests are more robust to cross-sectional dependence. The test results indicate whether the variables are stationary in their levels or first differences and ensure the correct specification of the model.
- **Model Selection (Hausman Test):** In panel data analysis, the assumption of whether the unit-specific effects ($mu(i)$) are random (Random Effects - RE) or fixed (Fixed Effects - FE) is critically important. The Hausman test is used to make a

statistically significant choice between these two models. The null hypothesis of the test is that the RE model is consistent. Rejection of this hypothesis indicates that there is a correlation between the explanatory variables and the unit-specific effects, and therefore the FE model, which provides consistent estimators, should be used.

- **Causality Analysis (Dumitrescu-Hurlin Panel Causality Test):** While regression analysis shows the relationship and correlation between variables, it does not provide information about the direction of causality. To answer the question, "Does automation cause unemployment, or do labor market dynamics trigger automation?" the panel causality test developed by Dumitrescu and Hurlin (2012) was used. This test is suitable for heterogeneous panel datasets and tests the null hypothesis "X is not a Granger cause of Y" for each panel unit individually (Dumitrescu & Hurlin, 2012).

4. Empirical Findings and Discussion

In this section, the empirical findings obtained using the defined econometric methods are presented, and these findings are discussed within the framework of the literature. The analysis begins with the results of the diagnostic tests, continues with the panel regression estimates, and concludes with the causality analysis.

4.1. Diagnostic Test Results

The results of the diagnostic tests necessary for the correct specification and estimation of the panel data model are summarized in Table 2 and Table 3.

Table 2: Cross-Sectional Dependence and Panel Unit Root Test Results

Test Type	**Variable**	**Statistic**	**Prob.**	**Conclusion**
Pesaran (2004) CD Test	-	5.82	0.0000	Cross-Sectional Dependence Exists
Im, Pesaran & Shin W-stat		**Level (Prob.)**	**First Difference (Prob.)**	**Order of Integration**
	Unemployment_Rate	0.812	0.001	I(1)
	Industrial_Automation_Level	0.955	0.000	I(1)
	ln(PC_GDP)	0.981	0.000	I(1)
	Mean_Years_Schooling	0.764	0.003	I(1)
	ln(Population)	0.992	0.000	I(1)

Note: For the CD test, H_0: No cross-sectional dependence. For the unit root test, H_0: All panels contain a unit root.

The Pesaran CD test result presented in the upper panel of Table 2 (Prob. < 0.01) indicates that the null hypothesis is strongly rejected and that there is significant cross-sectional dependence among the countries in the panel. This finding is expected as a result of globalization and economic integration and requires the use of standard errors robust to this dependence in the estimations.

The unit root test results in the lower panel of Table 2 reveal that all variables are non-stationary at their level values (prob. > 0.05) but become stationary when their first differences are taken (prob. < 0.01). This indicates that all series are integrated of order one, i.e., I(1). This situation fulfills a prerequisite for investigating the existence of a long-term relationship between the variables.

Table 3: Hausman Test Results (Model Selection)

Model	**Chi-Sq. Statistic**	**Prob.**	**Result**
Model 1 (Unemployment)	18.74	0.002	Fixed Effects (FE)

Note: H_0: Random effects model is consistent.

The results of the Hausman test, applied to choose between the Fixed Effects (FE) and Random Effects (RE) models, are shown in Table 3. The probability value (0.002) being less than the 1% significance level led to the rejection of the null hypothesis. This result indicates that the unobservable country-specific effects are correlated with the explanatory variables, and therefore the Fixed Effects (FE) model, which provides consistent and unbiased estimators, should be used.

4.2. Panel Regression Results

In line with the guidance from the diagnostic tests, the results of the Fixed Effects model, which includes country and year fixed effects and is estimated with standard errors robust to cross-sectional dependence (Driscoll-Kraay), are presented in Table 4.

Table 4: Panel Data Regression Results (Fixed Effects Model)

Variables	Model 1: Unemployment_Rate
Industrial_Automation_Level	**0.0042****
	(0.0019)
ln(PC_GDP)	**-2.851*****
	(0.745)
Mean_Years_Schooling	**-0.512***
	(0.298)
ln(Population)	0.987
	(0.650)
Constant	15.234***
	(3.112)
Observations	380
R-squared (within)	0.689
Fixed Effects	Country and Year

Note: Values in parentheses indicate Driscoll-Kraay robust standard errors. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

The results in Table 4 provide an empirical answer to the study's main research question. The coefficient of the main independent variable, Industrial_Automation_Level (0.0042), is positive and statistically significant at the 5% level. The interpretation of this finding is as follows: holding all other factors constant, a 100-unit increase in a country's automation level in the manufacturing industry (i.e., 100 additional robots per 10,000 employees) is associated with an increase of approximately 0.42 percentage points in the national unemployment rate. This result indicates that the net effect of automation, at least for the period and group of countries examined, is in the direction of displacement and creates visible pressure in the labor market. Although the magnitude of the effect is not dramatic, its statistical significance shows that automation is a factor to be considered in unemployment dynamics.

The coefficients of the control variables also yielded results consistent with economic theory. The coefficient of the ln(PC_GDP) variable (-2.851) is negative and significant at the 1% level, as expected. This is consistent with Okun's Law, confirming that economic growth and increased prosperity have an unemployment-reducing effect. The coefficient of the Mean_Years_Schooling variable (-0.512) is also negative and significant at the 10% level. This suggests that countries with a higher human capital stock adapt better to technological changes and have more flexible labor markets. The coefficient of the ln(Population) variable was found to be statistically insignificant, indicating that after controlling for other factors in the model, population size alone does not have a decisive effect on the unemployment rate.

4.3. Panel Causality Analysis

The Dumitrescu-Hurlin panel causality test was applied to determine the direction of the causal relationship between the variables. The test results are summarized in Table 5.

Table 5: Dumitrescu-Hurlin Panel Causality Test Results

Null Hypothesis (H_0)	W-Stat	Z-bar Stat	Prob.	Result
Industrial Automation Level does not Granger-cause Unemployment Rate	4.115	2.876	0.004	Causality Exists
Unemployment Rate does not Granger-cause Industrial Automation Level	1.982	0.954	0.340	No Causality

The causality test results are quite clear. In the first row, which tests the hypothesis of causality from Industrial_Automation_Level to Unemployment_Rate, the probability value (0.004) is less than the 1% significance level. Therefore, the null hypothesis "Industrial automation level is not a Granger cause of the unemployment rate" is rejected. In contrast, in the second row, the probability value (0.340) for the hypothesis testing causality from the unemployment rate to the industrial automation level is insignificant, and the null hypothesis cannot be rejected.

These findings strongly support the existence of a unidirectional causal relationship between the industrial automation level and the unemployment rate. That is, increases in the automation level cause increases in future unemployment rates; however, changes in unemployment rates do not significantly affect automation investments. This result reinforces the regression findings and shows that the observed positive relationship is not just a correlation, but that automation is a causal driving force on labor market outcomes.

4.4. Discussion of Findings

The empirical findings of this study show that increased industrial automation led to a statistically significant and causal increase in unemployment rates in the selected panel of countries for the 2005-2023 period. This result aligns more with the findings of Acemoglu and Restrepo (2020), which emphasize the displacement effect, within the "great divide" in the literature. This country-level analysis indicates that the adverse effects observed in local labor markets may be strong enough to create a net negative impact at the national level, at least for this group of countries.

There are several potential reasons why these findings diverge from the study by Graetz and Michaels (2018), which found a neutral effect on total employment. First, this study covers a more recent period (up to 2023), and it is possible that as the spread of automation technologies has accelerated in recent years, the displacement effects have become more dominant than the productivity effects. Second, the unit of analysis is different. While Graetz and Michaels conducted an industry-level analysis, this study examines macroeconomic effects at the country level. A country-level analysis may better capture the frictional unemployment and adjustment costs created by inter-industry labor shifts (e.g., the transition from manufacturing to services).

However, two important points are critical to consider when interpreting these results. The first is the "unit of analysis dilemma." Although the country-level findings of this study show that automation creates a net macroeconomic challenge, they do not provide information about the distribution of this effect within the country. Acemoglu and Restrepo's local-level analysis showed that the effects of automation are concentrated in specific geographical regions and demographic groups (Acemoglu & Restrepo, 2020). Therefore, the modest macro effect found may be masking much more severe job losses and social problems experienced in specific manufacturing regions. A decrease in employment in one sector at the national level while it increases in another does not mean that a worker who lost their job found a new one; this process can lead to long-term unemployment due to geographical and skill mismatches. Therefore, the net effect at the macro level may not reflect the full picture of the individual and regional-level turmoil created by automation.

Second, and more importantly, is the "measurement gap" problem. This study, like many in the literature, measures automation by "industrial robot density" (termed "industrial automation level" in this study) due to data constraints. This variable primarily reflects the automation of routine *manual* tasks in the manufacturing sector (Acemoglu & Restrepo, 2020). However, the current AI revolution, especially with generative AI (like LLMs), is targeting routine *cognitive* tasks in the service sectors (writing, summarizing, coding, customer service) (Brynjolfsson & McAfee, 2014). The workforce profile affected by this new wave of technology (high-skilled, white-collar, early-career employees) (PwC, 2025) is quite different from the profile affected by industrial robots. Therefore, the findings of this study should be seen as an analysis of the previous wave of automation. The findings cannot be directly used to predict the future effects of generative AI, and the impacts of this new wave on labor markets need to be examined separately with new datasets.

5. Conclusion and Policy Recommendations

This study examined the impact of the industrial automation level, as a proxy for artificial intelligence adoption, on unemployment in selected 20 countries for the 2005-2023 period using panel data methods. The analyses, conducted using the Fixed Effects model and the Dumitrescu-Hurlin causality test, concluded that increasing automation has a statistically significant, positive, and causal effect on unemployment rates. This finding provides empirical evidence that the displacement effects created by technology outweigh the productivity and new job creation effects, at least for the period and group of countries studied.

The results obtained reveal that automation poses a non-negligible challenge for labor markets and that policymakers must proactively manage this technological transformation. Although the magnitude of the effect is modest, its consistent direction towards negative employment outcomes suggests that the cost of inaction could be high. In light of these findings and the discussions in the literature, the following policy recommendations can be developed:

1. **Investment in Human Capital and Reskilling:** The findings show that higher education levels have a reducing effect on unemployment. Therefore, the policy priority should be to equip the workforce with the skills required for the automation age. Governments and the private sector must support educational curricula and vocational training programs that focus on skills that are difficult to replace with AI, such as critical thinking, creativity, problem-solving, and digital literacy (Brynjolfsson & McAfee, 2014; PwC, 2025).
2. **Promotion of a Lifelong Learning Culture:** The pace of technological change means that a one-time education will not be sufficient for an entire career. Public-private partnerships should be established for flexible and accessible lifelong learning opportunities (e.g., micro-credentials, online courses) that enable employees to acquire new skills and update their existing ones throughout their careers (Brynjolfsson & McAfee, 2014).
3. **Strengthening and Modernizing Social Security Systems:** Social safety nets must be strengthened to support workers who lose their jobs during the transition created by automation. This may include expanding the duration and coverage of unemployment insurance and facilitating access to active labor market programs (job search counseling, training support). More radical proposals, such as Universal Basic Income (UBI), should also be discussed and tested with pilot programs as a tool to mitigate the social costs of this transformation (Murat & Şengül, 2022).
4. **Targeted Support Mechanisms:** Analyses show that the effects of automation are not homogeneous but are concentrated in specific sectors (manufacturing) and skill groups (low-skilled). Therefore, policies should focus on these most vulnerable groups. Special investment and employment incentives can be provided for a regions most affected by automation through regional development agencies. Special programs should be designed for the reskilling of low-skilled and older workers (Çetin & Kutlu, 2025; PwC, 2025).

In conclusion, the findings of this study paint a complex picture in which artificial intelligence and automation present both a threat and an opportunity for employment. Technology itself is not destiny; its effects will depend on how we manage it and how we adapt as a society. With smart, forward-thinking, and human-centric policies, it is possible to manage the challenges posed by the Fourth Industrial Revolution and spread its benefits to society at large.

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