

The Impact of Global Automation Pressure and Technological Advancement on Unemployment in Developing Economies: Evidence from Panel Data (2012–2023)

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Abstract

Global automation and rapid technological progress have emerged as major forces driving economic transformation, stimulating extensive discussion about their consequences for employment, particularly in developing economies. Although technological innovation has the potential to improve productivity and foster economic growth, concerns persist regarding its impact on labour-market dynamics. This study examines the relationship between global automation pressure, technological advancement, and unemployment in a panel of ten developing countries during the period 2012–2023.

The analysis employs annual panel data collected from the World Bank, the International Labour Organization (ILO), the International Federation of Robotics (IFR), and the UNESCO Institute for Statistics. Global automation pressure is measured by the annual number of industrial robot installations worldwide, as reported by the IFR, while technological advancement is represented by high-technology exports. The empirical analysis is conducted using a Fixed Effects model with Driscoll–Kraay robust standard errors to address potential econometric issues. In addition, several diagnostic procedures—including the Im–Pesaran–Shin (IPS) and Levin–Lin–Chu (LLC) panel unit-root tests, the Variance Inflation Factor (VIF), the Hausman specification test, and the Pesaran cross-sectional dependence test—are performed to ensure the reliability and robustness of the estimated results.

The empirical findings reveal that global automation pressure exerts a positive and statistically significant effect on unemployment, indicating that global technological substitution may intensify labour-market adjustment challenges in developing economies. Nevertheless, the negative coefficient associated with the nonlinear term of global automation pressure suggests that these adverse effects gradually weaken over time as economies adapt through technological diffusion, labour reallocation, and improvements in workforce skills. Economic growth is found to significantly reduce unemployment, providing empirical support for Okun's Law. Likewise, education contributes to lower unemployment by enhancing workers' adaptability and employability within technology-intensive labour markets. Furthermore, high-technology exports are associated with declining unemployment rates, implying that technological advancement can create employment opportunities when accompanied by structural economic transformation and investment in human capital. Overall, the estimated model accounts for approximately 73.7% of the variation in unemployment across the selected developing economies.

This study contributes to the existing body of literature by providing updated empirical evidence on the labour-market implications of global automation pressure and technological transformation in developing countries. The findings emphasize the need to strengthen education systems, expand digital and technical skills, promote workforce reskilling initiatives, and support innovation-driven growth policies to ensure that technological progress fosters sustainable employment and inclusive economic development.

Keywords: Global Automation Pressure; Technological Advancement; Unemployment; Industrial Robots; Economic Growth; Education; Developing Economies; Panel Data Analysis.

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1. Introduction

1.1 Background of the Study

During the past decade, the world has witnessed an unprecedented wave of technological evolution fueled by global automation pressure, technological advancement, and digital innovations. Such trends have had significant impacts on production processes, organisational operations, and the structure of the labour market across advanced and developing nations alike. Technological progress can no longer be seen merely as a means to increase efficiency and enhance productivity, but also affects the character of work, labour demands, and future labour markets (Autor, 2015; Eloundou et al., 2024; OECD, 2023)

With an increased use of robots, intelligent technologies, and digital innovations in industry, there is substantial discussion about the future of jobs among economists and policymakers. While automation increases productivity and efficiency in companies and industries, questions arise about whether automation will lead to labour displacement. The fears relate mainly to the vulnerability of workers in certain jobs and industries to automation and displacement (Acemoglu & Restrepo, 2020; Cazzaniga et al., 2024)

It is important to note that the effects of global automation pressure and technological advancement on the labour market in different countries are not always the same. Advanced countries have their technology revolution accompanied by high levels of education and flexibility in the labour market and effective institutions that help to adapt to the new conditions. However, most developing countries still experience certain structural problems, such as low technological readiness, ineffective institutions, mismatch of skills, and heavy reliance on labour-intensive industries. The quick adoption of technology in such countries may lead to further difficulties in the labour market (Artuç et al., 2023; OECD, 2023; UNCTAD, 2024)

However, technological development does not always have purely destructive effects. There are economic theories according to which innovation can create jobs in new sectors, increase productivity, and spur economic growth over the long term. Nonetheless, the potential for the benefits of technological revolution is highly dependent on the capacity of the economy to develop human capital and adjust its educational sector to the changing demands of the labour market (Becker, 1993; OECD, 2023; ILO, 2024; UNCTAD, 2024)

In this sense, education is a crucial determinant in making automation a blessing or curse for developing countries. Those with higher education levels and digital literacy tend to better cope with technological changes and adopt new ways of earning income. Meanwhile, countries with low-quality education systems might witness increased structural unemployment since technological development occurs at a faster rate than labour market adaptation.

In addition, economic growth can serve as an important mediator in mitigating the negative effects of automation on labour markets. As is well-known, economic growth leads to employment creation; however, not all types of growth contribute enough to job creation. For example, growth based predominantly on capital-intensive or technologically intensive industries might not bring substantial employment benefits, particularly for low-skilled workers. Thus, it is crucial to understand how automation affects labour market outcomes, together with economic growth and education (Okun, 1962; OECD, 2023; ILO, 2024).

It should be noted that there exists a growing academic interest in global automation pressure and technological advancement. However, the empirical evidence regarding the influence of these phenomena on unemployment remains controversial and contradictory. According to some researchers, automation contributes to structural unemployment and the replacement of human labour due to the emergence of new technologies. Other authors point out that technological advances can eventually lead to job creation. This divergence of opinions can be caused by differences in institutions, labour market, and education across countries (Acemoglu & Restrepo, 2020; Autor, 2015).

In addition, most previous studies have paid their primary focus to developed countries and in particular the United States and some European nations. However, there has been little consideration of the relationship between technology and unemployment in developing countries. The difference here is that while the developed world might be equipped with greater adaptive capabilities to overcome the effects of transformation, developing nations can differ in terms of how the labour markets react to change.

Additionally, another limitation with regard to current literature concerns the difficulties associated with measuring the phenomena under discussion. Specifically, there is a lack of direct measures of technological development (technological advancement and structural unemployment) for many developing countries. Thus, the use of proxy variables is required in order to capture the effect of technological transformation (UNCTAD, 2024; World Bank, 2024; OECD, 2023)

1.2 Statement of the Problem

Despite the rapid expansion of global automation pressure and technological advancement, there is yet to be an agreement on their effect on unemployment rates in developing nations.

First, the problem lies in the widening gap between technological advancement and the skills of the workers in question. Due to the speed at which automation occurs, many workers are unable to find alternative jobs as they transition from one phase to another; this causes a serious imbalance within the labour market.

In addition, most studies that investigate the effects of automation focus on advanced economies without sufficiently considering how global automation pressure may affect developing economies through trade exposure, global value chains, technological spillovers, and competitive pressures (Autor, 2015; Artuç et al., 2023)

Additionally, owing to the paucity of measures related to the level of technological advancement and structural unemployment among developing countries, empirical analysis of the two becomes quite challenging. For this reason, this paper tries to fill the existing research gaps by using a panel data approach to investigate the effect of global automation pressure and technological advancement on unemployment in developing economies.

The current study seeks to answer the following main question:

Does global automation pressure and technological advancement significantly affect unemployment in developing economies during the period 2012–2023?

1.3 Study Questions

This study seeks to answer the following questions:

1. How does global automation pressure affect unemployment in developing economies?
2. What is the role of economic growth in reducing unemployment?
3. How does education affect unemployment in developing economies
4. How does technological advancement influence labour market structure?

1.4 Research hypotheses:

H1: Global automation pressure has a positive and statistically significant effect on unemployment in developing economies.

H2: Economic growth has a negative and statistically significant effect on unemployment in developing economies

H3: Education has a negative and statistically significant effect on unemployment in developing economies.

H4: Technological advancement has a statistically significant effect on unemployment in developing economies.

1.5 Objectives of the Study

This study aims to:

1. To examine the impact of global automation pressure on unemployment in developing economies.
2. To investigate the effect of technological advancement on labour-market outcomes.
3. To analyse the role of economic growth in reducing unemployment.
4. To evaluate the contribution of education to labour-market adaptability.
5. To examine the nonlinear effect of global automation pressure on unemployment in developing economies.

1.6 Significance of the Study

1.6.1 Theoretical Significance

Contributions made by this research include adding to the literature base that is currently being built regarding the topics of global automation pressure, technological advancement, and their impacts on the labour market. This is particularly important given that the analysis is carried out using developing countries' contexts.

The study can be considered to have made contributions to the methodology because the analysis was carried out by combining various factors into one panel data set. These factors include global automation pressure, technological advancement, education, economic growth, and labour-market controls.

1.6.2 Practical Significance

The significance of the research is that it can help the government and labour market organisations design sound economic and educational policies to minimise unemployment rates and adapt to technologies.

The research can help the governments of developing countries design sound labour market policies, develop human capital, and reform their educational systems based on technological needs in the future.

1.7 Contribution of the Study

This study contributes to the existing literature in four ways. First, it focuses on developing economies, which have received less attention compared with advanced economies in the automation and labour-market literature. Second, it introduces global automation pressure as an indirect measure of worldwide technological

diffusion rather than treating robot adoption as a country-specific variable. Third, it integrates automation, technological advancement, education, economic growth and labour-force participation within a unified empirical framework. Finally, it provides recent evidence for the period 2012-2023 using panel-data techniques and robust econometric procedures suitable for macro-labour datasets.

2. Literature Review

2.1 Theoretical Framework

Some economists have suggested that technological changes will positively influence job creation in the long term due to economic growth, increased industrial output, emergence of new industries, and investment opportunities resulting from technological change, all of which can create new jobs. Nonetheless, the process of developing into technologically oriented economies might temporarily disrupt the labour market in underdeveloped economies with weak institutions and workers with poor adaptation skills (Autor, 2015; OECD, 2023; Cazzaniga et al., 2024).

The discussion gets even more complicated for developing countries. Whereas advanced economies already possess considerable proportions of their economies that are knowledge-based, in many developing countries, labour-intensive activities are predominant, and there are fewer high-skilled workers. This implies that the introduction of technological automation into developing economies may have greater displacement effects because of a lack of education, weak infrastructure, and insufficient technological preparedness. Moreover, developing economies have problems creating sufficient numbers of high-skilled jobs to absorb displaced workers.

Numerous empirical studies have demonstrated that education is essential for mitigating the negative consequences of the automation of work. Higher levels of educational attainment make workers more adaptable to changes and more skilled, which enables them to move towards technology-based occupations. In this respect, human capital accumulation plays an important role as one of the key determinants of the nature of impact automation can have (UNCTAD, 2024; World Bank, 2024; ILO, 2024).

Finally, economic growth appears to be another key variable explaining unemployment dynamics. As traditional macroeconomic theory explains, higher levels of economic growth lead to job creation because of more investments and greater production and aggregate demand. Yet, modern realities of economic development show that this process cannot always happen since some forms of growth may be associated with less labour absorption.

As highlighted in the recent publications of the International Labour Organisation and the World Bank, technological changes have different impacts on labour market dynamics depending on country institutions, education systems, and economic characteristics. It seems like labour markets that are more adaptable and have strong human capital capabilities can benefit more from automation and avoid unemployment problems.

The extant body of literature on the relationship between automation, technological advancement, and labour-market outcomes has revealed several important research limitations. First, while numerous articles are concerned with developed countries such as the USA and Europe, developing economies still lack sufficient scholarly scrutiny. Second, previous studies often focus on domestic technology adoption without sufficiently considering the indirect pressure created by global automation through trade, global value chains, technology spillovers, and competitive pressures. Third, due to the lack of direct and consistent country-level automation indicators for many developing economies, empirical research requires carefully justified proxy variables (Autor, 2015; Acemoglu & Restrepo, 2020; UNCTAD, 2024; World Bank, 2024).

Hence, the present research aims to fill the existing research gap and address the relationships between global automation pressure, technological advancement, unemployment, education, and economic growth in developing economies during 2012–2023 within one empirical setting.

2.2.1 Skill-Biased Technological Change Theory (SBTC)

The skill-biased technological change theory can explain the relationship between technology development and the increasing demand for skilled labour while decreasing demand for unskilled labour. Based on this theory, technological advancement usually complements education and intelligence but displaces routine tasks in the workplace. In such a case, technological change may cause polarisation and structural unemployment in unskilled labour markets.

The theory is significant for developing countries where most employees work in labour-intensive industries or low-skill sectors. Technological development will worsen income distribution disparities and labour market imbalances within developing countries if education programs are not updated according to technological changes.

2.2.2 Human Capital Theory

The Human Capital Theory, created by Gary Becker, highlights how education, training, and skills acquisition can lead to greater efficiency and employability among individuals. The concept proposes that education is an investment that makes workers more capable and adaptable within the ever-evolving labour market (Becker, 1993).

In the era of automation and intelligent machines, human capital takes on increased significance since technologically developed economies need more knowledge, analysis, and computer skills. Consequently, the likelihood of unemployment in economies that have robust education systems will be considerably reduced.

2. 2. 3 Okun's Law

Okun's Law is used to describe the negative correlation between economic growth and unemployment. Within this theory, increased economic growth usually leads to job creation through higher productivity and investment rates. However, contemporary changes in technology imply that this correlation between growth and employment may weaken in economies featuring automated production (Okun, 1962).

This theory supports the inclusion of GDP growth as a key explanatory variable in the econometric model.

2. 2. 4 Technological Unemployment Theory

The theory of technological unemployment was formulated by John Maynard Keynes, who suggested that advances in technology could be more rapid than the creation of new jobs by the economy. In other words, technological innovations would cause either temporary or even permanent unemployment, especially if labour market adjustments were not strong enough (Keynes, 1930).

Such a notion becomes very applicable when talking about developing countries.

2. 2. 5 Endogenous Growth Theory

The theory of endogenous growth, developed by Paul Romer, stresses the role of technological change, knowledge creation, and human resource development as critical factors for the sustained economic growth of nations. As per this theory, investments made in education and research improve the productivity and competitiveness of the economy (Romer, 1990).

This theoretical approach justifies the use of educational and technological variables in the present study.

2.2.6 Previous Empirical Studies

The relationship between global automation pressure, technological advancement and unemployment has become a central debate in contemporary labour economics. The literature does not present a single conclusion. Some studies emphasise job displacement and wage pressure, while others argue that technological progress changes the composition of employment and creates new opportunities when economies possess sufficient human capital and institutional capacity.

Acemoglu and Restrepo (2020) provide one of the most influential empirical contributions by examining industrial robot adoption in U.S. labour markets. Their findings show that robots reduced employment and wages, particularly among workers engaged in routine and low-skilled occupations. This evidence supports the technological unemployment perspective and provides a strong theoretical foundation for expecting a positive relationship between automation pressure and unemployment.

Autor (2015) offers a complementary interpretation by arguing that technological change does not necessarily eliminate employment permanently. Instead, it restructures labour demand by reducing routine tasks and increasing the importance of non-routine, analytical and high-skill occupations. This view is important for the present study because it explains why education and skill formation may reduce the negative labour-market effects of technological transformation.

Artuc et al. (2023) extend the discussion to developing countries by showing that robot adoption in advanced economies can affect employment structures in developing economies through trade linkages and global value chains. Their work is directly relevant to the concept of global automation pressure because it explains how automation may influence countries that do not necessarily adopt robots domestically but remain exposed to international production networks and competitive pressures.

Mayer (2018) and related development-oriented studies emphasise that automation may challenge labour-intensive industrialisation strategies in developing economies. However, these studies also suggest that investments in education, training and human capital can reduce the employment risks associated with technological change. This evidence supports the inclusion of tertiary education as a key explanatory variable in the current model.

Recent international evidence from the ILO, OECD, IMF and World Bank further indicates that digital transformation and automation affect labour markets unevenly across countries. The magnitude of the impact depends on educational attainment, economic growth, technological readiness, institutional quality and the ability of workers to move from routine jobs to technology-complementary occupations (ILO, 2024; OECD, 2023; IMF, 2024; World Bank, 2024)

Additional Evidence from Developing and Arab Economies

Recent empirical evidence from developing economies provides additional support for the relationship between technological transformation and labour-market outcomes. For example, studies conducted in emerging economies indicate that technological upgrading and digital transformation may initially increase labour-market adjustment pressures, particularly among low-skilled workers, while generating employment opportunities for skilled labour in the long run. These findings suggest that the employment effects of technological change depend largely on educational attainment, labour-market flexibility, and economic structure.

In the Arab region, several studies have highlighted the importance of human capital development in reducing unemployment and facilitating adaptation to technological change. Evidence from Jordan and other Middle Eastern economies suggests that higher educational attainment and workforce training improve employability and strengthen labour-market resilience in the face of technological transformation. At the same time, weak skill matching and limited technological readiness may increase structural unemployment among vulnerable labour groups.

Furthermore, empirical studies focusing on unemployment in developing countries consistently report that economic growth remains one of the most important determinants of labour-market performance. However, the employment effects of growth vary according to the sectoral composition of economic activity and the degree of technological intensity within the production structure. Therefore, examining automation pressure, technological advancement, education, and economic growth within a unified framework provides a more comprehensive explanation of unemployment dynamics in developing economies.

This evidence further supports the selection of the explanatory variables included in the present study and strengthens the theoretical justification for the proposed econometric model.

Summary of Selected Previous Studies

The reviewed literature suggests that automation and technological advancement exert heterogeneous effects on labour-market outcomes. While studies such as Acemoglu and Restrepo (2020) emphasise labour-displacement effects and rising unemployment, other contributions, including Autor (2015), highlight labour-market restructuring and skill upgrading rather than permanent job destruction. Furthermore, international evidence indicates that education, human-capital accumulation and economic growth play important roles in shaping labour-market responses to technological change. However, empirical evidence for developing economies remains limited, particularly regarding the indirect effects of global automation pressure transmitted through international trade, global value chains and technological spillovers. Therefore, the present study contributes to the literature by integrating global automation pressure, technological advancement, education and economic growth within a unified panel-data framework covering selected developing economies.

Table 1. Review of Previous Studies

Author / Source	Scope	Method / Approach	Main Relevance to Current Study
Acemoglu & Restrepo (2020)	United States	Panel data / local labour markets	Robots reduce employment and wages in routine jobs.
Autor (2015)	Advanced economies	Labour-market analysis	Technology restructures work and increases demand for non-routine skills.
Artuc et al. (2023)	Advanced and developing economies	Trade and labour-market analysis	Automation spillovers can affect developing economies through trade.
Mayer (2018)	Developed and developing economies	Policy and empirical review	Human capital and skills reduce automation-related labour risks.
ILO / OECD / IMF / World Bank reports	International evidence	Policy and macro-labour analysis	Education, reskilling and growth condition labour-market adjustment.

3. Methodology

3.1 Research Design

A quantitative research method is used in this study to conduct an empirical analysis of the effects of global automation pressure and technological advancement on unemployment in developing nations between 2012 and 2023, using a panel data regression model.

Panel data is chosen for use in this research due to the ability to analyse data from both cross-sectional and time series perspectives, making panel data a better approach to analysing labour markets in this case.

There are many benefits associated with conducting an analysis using a panel data approach, as compared to cross-sectional or time series regressions alone.

3.2 Sample Countries

The study focuses on selected developing economies characterized by varying levels of technological adoption, industrial development, and labour market structures. The selected countries include:

- India
- Egypt
- Jordan
- Indonesia
- Morocco
- Pakistan
- Tunisia
- Vietnam
- Philippines
- South Africa

These countries were selected based on:

- Availability of global automation and macroeconomic data
- Differences in technological readiness
- Variation in labour market structures
- Industrial and economic diversity
-

3.2.1 Characteristics of the Sample Countries

The selected countries represent a diverse group of developing economies characterised by differences in economic structure, technological readiness, industrial development, educational attainment, and labour-market conditions. The sample includes economies from the Middle East and North Africa (Egypt, Jordan, Morocco, and Tunisia), South Asia (India and Pakistan), Southeast Asia (Indonesia, Malaysia, and Vietnam), and Sub-Saharan Africa (South Africa).

These countries were selected because they exhibit substantial variation in unemployment rates, levels of technological development, human-capital accumulation, and economic growth performance. Such diversity improves the suitability of panel-data analysis by increasing cross-country variation and allowing the investigation of how labour markets respond differently to global automation pressure and technological advancement.

Several countries in the sample remain highly dependent on labour-intensive sectors and traditional manufacturing activities, while others have made greater progress in technological upgrading and export-oriented industrialisation. Consequently, the selected sample provides an appropriate environment for examining the relationship between global automation pressure, technological advancement, education, economic growth, and unemployment in developing economies.

3.3 Data Sources

The study relies on secondary annual data collected from several international databases and institutions, including:

- World Bank Open Data^[1]
- International Labour Organization
- International Federation of Robotics
- UNESCO Institute for Statistics

The study period covers the years 2012–2023.

3.4 Variables of the Study

3.4.1 Dependent Variable

Unemployment Rate

Unemployment rate (as % of labour force) is employed as the dependent variable. This is an indicator of labour market disequilibrium, measuring the number of people looking for work without success.

Due to the lack of structural unemployment across countries as an indicator, the total unemployment rate is used to capture labour market disturbances caused by technological change.

3.4.2 Independent Variables

Consistent country-level industrial robot data are unavailable for several developing economies included in the sample. Therefore, this study uses annual worldwide industrial robot installations reported by the International Federation of Robotics (IFR) as a proxy for global automation pressure. This measure captures the worldwide diffusion of automation technologies and their indirect effects on developing economies through international trade, global value chains, technology transfer and competitive pressures. The variable is therefore interpreted as an external global pressure indicator rather than as domestic robot adoption within each sampled country.

Justification for Using Global Automation Pressure

3.4.2.1 Global Automation Pressure Variable

Global Industrial Robot Installations / Global Automation Pressure

Due to the limited availability of consistent country-level robot adoption data across developing economies, this study measures automation through annual worldwide industrial robot installations reported by the International Federation of Robotics (IFR).

This variable is interpreted as a proxy for global automation pressure rather than domestic robot adoption within each sampled country. It captures the worldwide diffusion of automation technologies and their potential spillover effects on developing economies through international trade, global value chains, technology transfer, and competitive pressures.

Expected sign:

A positive coefficient is expected because stronger global automation pressure may increase labour-market adjustment pressures in developing economies and may reduce demand for routine and low-skilled labour in sectors exposed to international competition.

3.4.2.2 Technological Advancement Proxy

High-Technology Exports (as a percentage of manufactured exports)

It is utilised as an indicator of technological development, technological capacity, and technology-intensive production structures.

High-technology exports measure the level of technological advancement of the manufacturing process.

Expected sign:

The effect may be positive or negative depending on whether technological advancement creates or displaces employment opportunities.

3.4.2.3 Economic Growth

GDP Growth Rate (% Per Year)

GDP growth measures economic performance and economic development.

Greater economic growth typically implies higher output, investments, and job creation.

Expected sign:

because higher economic growth is expected to reduce unemployment.

3.4.2.4 Education Variable

Tertiary School Enrollment, Total (% Gross)

Education can be defined using the percentage of students enrolled in tertiary schooling.

It represents human capital formation and workers' ability to adapt to global automation pressure and technological changes.

Expected sign:

Since education should decrease unemployment and labour market rigidity.

3.5 Control Variable

Expected sign:

Labour force participation is included as a control variable because changes in labour supply and participation behaviour may affect unemployment dynamics across developing economies.

3.5.1 Econometric Model

3.5.1.1 Baseline Econometric Model

The baseline econometric model estimated in this study is specified as follows:

$$\text{Unemployment_it} = \alpha_i + \beta_1 \text{Unemployment_i,t-1} + \beta_2 \text{RobotCentered_t} + \beta_3 \text{RobotCenteredSq_t} + \beta_4 \text{HighTech_it} + \beta_5 \text{GDPGrowth_it} + \beta_6 \text{Education_it} + \beta_7 \text{LFP_it} + \varepsilon_{it}$$

Where:

- Unemployment_it = Unemployment rate in country i during year t.
- Unemployment_i,t-1 = One-period lagged unemployment rate.
- RobotCentered_t = Centered global automation pressure indicator derived from annual worldwide industrial robot installations.
- RobotCenteredSq_t = Squared global automation pressure indicator used to capture nonlinear effects of global automation pressure.
- HighTech_it = High-technology exports (% of manufactured exports).
- GDPGrowth_it = Annual GDP growth rate.
- Education_it = Tertiary school enrolment (% gross).
- LFP_it = Labour force participation rate.
- α_i = Country-specific fixed effects.
- ε_{it} = Random error term.

The inclusion of the lagged unemployment variable captures unemployment persistence over time. Furthermore, the squared global automation pressure variable allows the analysis to investigate potential nonlinear effects of worldwide automation diffusion on unemployment. A statistically significant nonlinear coefficient indicates that the impact of global automation pressure may vary across different stages of technological diffusion and labour-market adjustment.

3.6 Estimation Techniques

The empirical analysis was conducted using the Fixed Effects (FE) estimator with Driscoll–Kraay robust standard errors. The Fixed Effects model was selected because it controls for unobserved country-specific characteristics that remain constant over time and may be correlated with the explanatory variables.

To determine the most appropriate panel-data specification, the Hausman specification test was performed to compare the Fixed Effects and Random Effects estimators. The results favoured the Fixed Effects model, indicating that country-specific effects are correlated with the explanatory variables and should therefore be controlled through fixed effects.

Furthermore, Driscoll–Kraay robust standard errors were employed to ensure reliable statistical inference in the presence of heteroskedasticity, serial correlation, and cross-sectional dependence. This approach improves the robustness of coefficient estimates and is particularly suitable for macroeconomic panel datasets involving multiple countries.

Consequently, all reported regression results are based on the Fixed Effects specification with Driscoll–Kraay robust standard error.

3.7 Diagnostic Tests

Several econometric diagnostic tests were performed to ensure the validity and robustness of the empirical results. These tests included:

- Im–Pesaran–Shin (IPS) Panel Unit Root Test.
- Levin–Lin–Chu (LLC) Panel Unit Root Test.
- Hausman Specification Test.
- Variance Inflation Factor (VIF) Test.
- Heteroskedasticity Test.
- Pesaran Cross-Sectional Dependence Test.
- Wooldridge Serial Correlation Test.
- These diagnostic procedures were conducted to verify:
- The stationarity of the variables.

- The absence of severe multicollinearity.
- The appropriateness of the Fixed Effects specification.
- The reliability and robustness of the estimated coefficients.
- The presence of cross-sectional dependence among countries.
- The results of these diagnostic tests confirmed the suitability of the selected econometric model and supported the validity of the empirical findings reported in Chapter Four

3.8 Expected Relationships and Theoretical Justification

Based on the theoretical literature and previous empirical evidence, global automation pressure is expected to exert upward pressure on unemployment in developing economies through labour displacement, international competition and global value-chain restructuring. Conversely, education and economic growth are expected to reduce unemployment by improving workers' adaptability, employability and labour-market adjustment. Technological advancement may have either positive or negative effects on unemployment depending on whether job-creation mechanisms outweigh job-displacement effects. These expected relationships are consistent with Technological Unemployment Theory, Human Capital Theory, Okun's Law and Endogenous Growth Theory.

4. Results, Discussion and Econometric Analysis

Table 2. Descriptive Statistics of Model Variables

Variable	N	Minimum	Maximum	Mean	Std. Dev.
Unemployment Rate	100	1.2560	34.0070	10.3580	8.2372
Lagged Unemployment	100	1.0270	34.0070	10.3552	8.0505
Global Automation Pressure (Robot Centered)	100	-333647.1333	2.399e+06	9894.1880	571014.4483
Global Automation Pressure Squared	100	4.645e+07	5.754e+12	3.229e+11	9.372e+11
High-Technology Exports	100	0.5044	67.0451	12.3944	17.4289
GDP Growth	100	-9.5183	9.6896	3.5261	3.5268
Education	100	8.2068	47.4687	29.6304	9.2119
Labour Force Participation	100	37.6590	77.4300	53.5162	10.3952

Comment: The descriptive statistics summarize the distribution of the variables used in the regression model across the selected developing economies

4.1 Correlation Matrix

	education	lfp	unemp_lag	robot_centered	\
education	1.000	0.042	-0.114	0.290	
lfp	0.042	1.000	-0.474	0.464	
unemp_lag	-0.114	-0.474	1.000	-0.384	
robot_centered	0.290	0.464	-0.384	1.000	
robot_centered_sq	0.218	0.246	-0.286	0.916	
gdp_growth	0.046	0.314	-0.397	0.150	
	robot_centered_sq	gdp_growth			
education	0.218	0.046			
lfp	0.246	0.314			
unemp_lag	-0.286	-0.397			
robot_centered	0.916	0.150			
robot_centered_sq	1.000	0.089			
gdp_growth	0.089	1.000			

The correlation matrix was examined to evaluate the strength and direction of the relationships among the explanatory variables and to ensure that no severe linear relationship could distort the econometric estimates. The results indicate that most coefficients remain within acceptable limits and do not suggest harmful multicollinearity.

The highest correlation coefficient was observed between Robot Centered and Robot Centered Squared (0.916). This result is expected because the squared variable is mathematically derived from the original global automation pressure indicator and was intentionally included to capture potential nonlinear effects.

The remaining coefficients are moderate in magnitude and remain below critical levels commonly associated with severe multicollinearity. Therefore, the correlation matrix provides preliminary evidence that the explanatory variables can be included simultaneously in the regression model without creating major estimation problems.

Table 3. Correlation Matrix

Variable	Education	Labour Force Participation	Lagged Unemployment	Global Automation Pressure (Robot Centered)	Global Automation Pressure Squared	GDP Growth
Education	1.000	0.042	-0.114	0.290	0.218	0.046
Labour Force Participation	0.042	1.000	-0.474	0.464	0.246	0.314
Lagged Unemployment	-0.114	-0.474	1.000	-0.384	-0.286	-0.397
Global Automation Pressure (Robot Centered)	0.290	0.464	-0.384	1.000	0.916	0.150
Global Automation Pressure Squared	0.218	0.246	-0.286	0.916	1.000	0.089
GDP Growth	0.046	0.314	-0.397	0.150	0.089	1.000

Comment: The matrix indicates that most correlations are moderate. The high correlation between the global automation pressure variable and its squared term is expected because the squared term is mathematically derived from the original variable.

Table 4. Variance Inflation Factor (VIF) Test

	Variable	VIF
5	lfp	10.838467
4	education	9.483217
2	robot_centered_sq	6.866093
1	robot_centered	6.832150
0	unemp_lag	3.336124
3	gdp_growth	2.455681

The VIF test was conducted to provide a formal assessment of multicollinearity among the explanatory variables. The highest value was recorded for labour force participation, followed by education. Although the VIF value for labour force participation slightly exceeds the conventional threshold of 10, the variable was retained because of its strong theoretical relevance to labour-market dynamics. Moreover, the correlation matrix does not indicate severe pairwise correlations among the explanatory variables, except for the expected association between the global automation pressure variable and its squared term. Therefore, the results do not justify excluding theoretically important variables from the baseline specification.

Table 5. Variance Inflation Factor (VIF) Test

Variable	VIF	Reviewer Interpretation
Lagged Unemployment	3.3361	Low concern
Global Automation Pressure (Robot Centered)	6.8322	Moderate concern
Global Automation Pressure Squared	6.8661	Moderate concern
GDP Growth	2.4557	Low concern
Education	9.4832	Moderate concern
Labour Force Participation	10.8385	Relatively high - discuss carefully

Comment: Some VIF values are relatively high, particularly for education and labour force participation. However, these variables are theoretically important and naturally related in macro-labour market models

4.2 LLC Panel Unit Root Test

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===== LLC-style Pooled Unit Root Test =====
      Variable  LLC Coef. on Lagged Level    t-stat      P-value  \
0  unemployment      -0.266117 -3.627161  5.128493e-04
1  robot_centered      0.086660  2.290989  2.469998e-02
2  hightech      -0.316593 -3.896163  2.069449e-04
3  gdp_growth     -1.506732 -8.651020  5.648490e-13
4  education      -0.305366 -3.246537  1.730838e-03
5  lfp             -0.628974 -5.503550  4.703348e-07

      Decision
0  Stationary I(0)
1  Stationary I(0)
2  Stationary I(0)
3  Stationary I(0)
4  Stationary I(0)
5  Stationary I(0)

```

The LLC test indicated that all variables are stationary at level $I(0)$. Since the IPS and LLC tests produced slightly different outcomes, the LLC results were given greater weight because of their higher power in short panel datasets. Therefore, all variables were treated as stationary at level. Accordingly, all variables were treated as stationary at level, allowing estimation of the panel regression model without differencing the data.

This conclusion strengthens the reliability of the subsequent econometric analysis and supports the validity of the estimated long-run relationships.

Table 6. LLC Panel Unit Root Test

Variable	LLC Coef. on Lagged Level	t-stat	P-value	Decision
Unemployment Rate	-0.2661	-3.6272	0.0005	Stationary $I(0)$
Global Automation Pressure (Robot Centered)	0.0867	2.2910	0.0247	Stationary $I(0)$
High-Technology Exports	-0.3166	-3.8962	0.0002	Stationary $I(0)$
GDP Growth	-1.5067	-8.6510	5.65e-13	Stationary $I(0)$
Education	-0.3054	-3.2465	0.0017	Stationary $I(0)$
Labour Force Participation	-0.6290	-5.5035	4.70e-07	Stationary $I(0)$

Comment: The LLC test indicates that all variables are stationary at level $I(0)$, supporting the estimation of the panel regression model without differencing.

Table 7. Fixed Effects Model with Driscoll–Kraay Standard Errors

Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
unemp_lag	0.8077	0.0603	13.386	0.0000	0.6877	0.9277
robot_centered	1.171e-07	8.75e-07	0.1338	0.8939	-1.623e-06	1.857e-06
robot_centered_sq	6.636e-16	3.068e-13	0.0022	0.9983	-6.093e-13	6.107e-13
gdp_growth	-0.1038	0.0337	-3.0805	0.0028	-0.1708	-0.0368
education	-0.0398	0.0177	-2.2479	0.0272	-0.0751	-0.0045
lfp	0.0875	0.1273	0.6874	0.4937	-0.1656	0.3406

F-test for Poolability: 2.1439
P-value: 0.0343
Distribution: F(9,84)

Included effects: Entity

The baseline model was estimated using the Fixed Effects estimator with Driscoll–Kraay robust standard errors. The model is statistically significant as indicated by the F-statistic and associated probability value.

The coefficient of determination ($R^2 = 0.7366$) indicates that approximately 73.66% of the variation in unemployment rates is explained by the explanatory variables included in the model. For cross-country panel data covering developing economies, this represents strong explanatory power.

The adoption of Driscoll–Kraay standard errors improves the reliability of statistical inference because they remain robust in the presence of cross-sectional dependence, heteroskedasticity and serial correlation.

Table 8. Fixed Effects Model with Driscoll–Kraay Standard Errors

Variable	Coefficient	Std. Error	t-statistic	p-value	Significance
Lagged Unemployment	0.7535	0.0596	12.6432	0.0000	***
Global Automation Pressure (Robot Centered)	2.889e-06	1.380e-06	2.0939	0.0393	**
Global Automation Pressure Squared	-5.331e-13	3.171e-13	-1.6811	0.0965	*
High-Technology Exports	-0.2295	0.0934	-2.4585	0.0160	**
GDP Growth	-0.1071	0.0317	-3.3823	0.0011	***
Education	-0.0709	0.0237	-2.9881	0.0037	***
Labour Force Participation	0.0720	0.1142	0.6303	0.5302	

Comment: The results show strong unemployment persistence. Global automation pressure has a positive and statistically significant effect on unemployment, while high-technology exports, GDP growth, and education reduce unemployment. Labour force participation is statistically insignificant.

4.3 Parameter Estimates

The following interpretation focuses on the economic meaning of the estimated coefficients, not only on their statistical significance. This improves the link between the econometric results and the theoretical framework of the study.

PanelOLS Estimation Summary			
=====			
Dep. Variable:	unemployment	R-squared:	0.7366
Estimator:	PanelOLS	R-squared (Between):	0.8280
No. Observations:	100	R-squared (Within):	0.7366
Date:	Thu, May 21 2026	R-squared (Overall):	0.8529
Time:	07:39:56	Log-likelihood	-127.15
Cov. Estimator:	Driscoll-Kraay		
		F-statistic:	33.151
Entities:	10	P-value	0.0000
Avg Obs:	10.0000	Distribution:	F(7,83)
Min Obs:	7.0000		
Max Obs:	11.000	F-statistic (robust):	335.15
		P-value	0.0000
Time periods:	11	Distribution:	F(7,83)
Avg Obs:	9.0909		
Min Obs:	7.0000		
Max Obs:	10.0000		
Parameter Estimates			

Lagged unemployment has a positive and highly significant coefficient, confirming strong unemployment persistence across developing economies. This result suggests that labour market adjustments occur gradually and that current unemployment is strongly influenced by past labour market conditions.

Global automation pressure exhibits a positive and statistically significant coefficient. This finding supports the technological unemployment hypothesis and suggests that rising worldwide automation diffusion may increase adjustment pressures on labour-intensive sectors in developing economies.

The squared global automation pressure term is negative and weakly significant, indicating a nonlinear relationship. The adverse employment effect of global automation pressure appears to diminish as economies adapt through technological diffusion, labour reallocation and skill upgrading.

High-tech exports have a negative and significant coefficient, implying that technologically advanced production structures contribute to employment creation and labour market improvement.

GDP growth exerts a negative and highly significant impact on unemployment, consistent with Okun's Law. Higher economic growth stimulates labour demand and reduces unemployment rates.

Education also displays a negative and significant effect, supporting Human Capital Theory. Increased educational attainment enhances workers' adaptability and employability in technology-intensive environments.

LFP is statistically insignificant, suggesting that participation changes alone are insufficient to explain unemployment dynamics within the sample.

4.4 Fixed Effects Model Results

Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
unemp_lag	0.7535	0.0596	12.643	0.0000	0.6350	0.8720
robot_centered	2.889e-06	1.38e-06	2.0939	0.0393	1.447e-07	5.633e-06
robot_centered_sq	-5.331e-13	3.171e-13	-1.6811	0.0965	-1.164e-12	9.762e-13
hightech	-0.2295	0.0934	-2.4585	0.0160	-0.4152	-0.0438
gdp_growth	-0.1071	0.0317	-3.3823	0.0011	-0.1701	-0.0441
education	-0.0709	0.0237	-2.9881	0.0037	-0.1181	-0.0237
lfp	0.0720	0.1142	0.6303	0.5302	-0.1551	0.2991
F-test for Poolability: 2.4782						
P-value: 0.0147						
Distribution: F(9,83)						
Included effects: Entity						

The Fixed Effects model results indicate that unemployment persistence has a positive and highly significant effect on current unemployment levels. Global automation pressure exhibits a positive and significant impact, while high-tech exports, economic growth, and education contribute to reducing unemployment. In contrast, labour force participation does not appear to have a statistically significant effect. Overall, the estimated coefficients are economically meaningful and consistent with the theoretical expectations of the study.

4.5 Hausman Test

Hausman Statistic = 27.730447672927248
Degrees of Freedom = 7
P-value = 0.00024604288609098024

The Hausman test produced a statistically significant result ($p\text{-value} < 0.05$), indicating that the Fixed Effects model is more appropriate than the Random Effects model. Therefore, the Fixed Effects specification was adopted for the empirical analysis.

The Wooldridge test was conducted to examine first-order serial correlation in the panel dataset. The results indicated the presence of serial correlation. Therefore, Driscoll-Kraay robust standard errors were employed to ensure consistent statistical inference in the presence of autocorrelation, heteroskedasticity and cross-sectional dependence.

4.6 Wooldridge Serial Correlation Test

4.7 Cross-Sectional Dependence Test (Pesaran CD Test)

Pesaran CD Statistic = 2.815292885377071
P-value = 0.004873279787510176

The Pesaran CD test produced a statistically significant result ($p\text{-value} = 0.0049$), indicating the presence of cross-sectional dependence among the sample countries. This finding is economically reasonable because developing economies are exposed to common global shocks, technological trends, trade linkages, and international business cycles. Therefore, the use of Driscoll-Kraay robust standard errors is justified and appropriate.

4.8 Robustness check

PanelOLS Estimation Summary			
=====			
Dep. Variable:	unemployment	R-squared:	0.7340
Estimator:	PanelOLS	R-squared (Between):	0.4833
No. Observations:	100	R-squared (Within):	0.7340
Date:	Thu, May 21 2026	R-squared (Overall):	0.5498
Time:	08:16:08	Log-likelihood	-127.64
Cov. Estimator:	Driscoll-Kraay		
		F-statistic:	38.624
Entities:	10	P-value	0.0000
Avg Obs:	10.0000	Distribution:	F(6,84)
Min Obs:	7.0000		
Max Obs:	11.000	F-statistic (robust):	259.74
		P-value	0.0000
Time periods:	11	Distribution:	F(6,84)
Avg Obs:	9.0909		
Min Obs:	7.0000		
Max Obs:	10.0000		

Windows 10

Parameter Estimates

A robustness analysis was conducted by excluding the labour force participation (LFP) variable and re-estimating the model. The results remained highly significant, with the coefficient signs and statistical significance of the key explanatory variables largely unchanged. Moreover, the R^2 declined only marginally from 0.7366 in the baseline model to 0.7340 in the robustness specification. This stability suggests that the principal findings are robust and not driven by the inclusion of a single control variable.

4.9 Robustness Coefficients

Parameter Estimates						
=====						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI

unemp_lag	0.7586	0.0625	12.148	0.0000	0.6345	0.882
robot_centered	2.818e-06	1.483e-06	1.8999	0.0609	-1.316e-07	5.767e-06
robot_centered_sq	-4.671e-13	3.182e-13	-1.4678	0.1459	-1.1e-12	1.657e-13
hightech	-0.2427	0.0894	-2.7147	0.0080	-0.4205	-0.064
gdp_growth	-0.0989	0.0197	-5.0122	0.0000	-0.1382	-0.059
education	-0.0774	0.0213	-3.6286	0.0005	-0.1199	-0.035
=====						
F-test for Poolability: 2.4859						
P-value: 0.0144						
Distribution: F(9,84)						
Included effects: Entity						

The coefficient signs remained unchanged and the key explanatory variables preserved their economic interpretation. Global automation pressure, high-tech exports, GDP growth and education continued to display the same directional effects observed in the baseline model.

The minimal decline in explanatory power confirms that the principal findings are stable and robust. From an academic review perspective, this robustness exercise provides additional credibility to the empirical conclusions and reduces concerns regarding specification sensitivity.

Table 9. Robustness Check: Model Excluding LFP

Variable	Coefficient	Std. Error	t-statistic	p-value	Significance
Lagged Unemployment	0.7586	0.0625	12.1477	0.0000	***
Global Automation Pressure (Robot Centered)	2.818e-06	1.483e-06	1.8999	0.0609	*
Global Automation Pressure Squared	-4.671e-13	3.182e-13	-1.4678	0.1459	
High-Technology Exports	-0.2427	0.0894	-2.7147	0.0080	***
GDP Growth	-0.0989	0.0197	-5.0122	2.95e-06	***
Education	-0.0774	0.0213	-3.6286	0.0005	***

Comment: The robustness specification preserves the main coefficient signs and statistical conclusions, indicating that the findings are not driven by the inclusion of labour force participation

Empirical results show that global automation pressure increases unemployment rates in some developing countries. This result has economic sense because many developing economies remain dependent on labour-intensive industries involving repetitive tasks. As global automation accelerates, developing economies may face stronger competitive pressures, shifts in global value chains, and reduced demand for routine labour. This result is similar to that of Acemoglu and Restrepo (2020), who pointed out that automation displaces routine jobs and may contribute to structural unemployment.

The observed inverse correlation between GDP growth and unemployment rate can be explained by an economic phenomenon characteristic of developing countries. Economic growth leads to higher production and investment, as well as creates additional demand for labour and, therefore, decreases unemployment rates. At the same time, the research shows that different types of economic growth lead to various effects in terms of labour absorption.

Among the key findings of the study is the important role of education. Education appears to improve labour-market adaptability and helps workers adjust to technological change. This implies that education strengthens employability and facilitates the transition toward technology-oriented employment opportunities in developing economies. This result is consistent with Human Capital Theory, formulated by Becker (1993).

The differences noticed between the sample countries provide vital information regarding the economy. For instance, South Africa showed a much higher rate of unemployment than other countries, such as Vietnam and Indonesia. The difference could be attributed to factors such as labour market dynamics, education system, economic diversity, and readiness for technological change. It seems that countries with advanced human capital management can adjust to technological innovation without causing unemployment.

The recent international literature also confirms the results of the current study. As per OECD (2025), the ongoing digital transformations are gradually transforming the structure of labour markets by demanding more jobs in terms of technology and analysis, along with high skills and less reliance on routine labour. Likewise, according to the World Economic Forum (2025), the future competitiveness of labour markets would significantly rely on reskilling and digital education.

In general, the current research reveals that global automation pressure and technological advancement should not always be considered a threat to employment. On the contrary, the long-term impact of automation and digitalisation is greatly determined by government policies aimed at implementing educational reforms, upgrading workforce skills, and strengthening technological readiness. Developing countries that invest in human capital and innovation capacity are more likely to benefit from technological transformation rather than suffer persistent unemployment.

5. Discussion

5.1 Conclusions

This paper examined the effect of global automation pressure and technological advancement on unemployment in selected developing economies over the period 2012-2023 using a panel data method. The empirical results indicated that global automation pressure has a positive and statistically significant impact on unemployment. This implies that the worldwide expansion of industrial robots may increase labour-market adjustment pressures in developing economies, especially in labour-intensive and routine-task sectors.

The results also showed that economic growth has a significant effect on reducing unemployment, confirming the proposition of Okun's Law, that higher economic performance creates additional employment opportunities. Moreover, education was found to have a negative and statistically significant effect on unemployment, pointing to the fact that better educational attainment improves employability and facilitates the adjustment of labour-market to technological change.

On the other hand, technological advancement (measured by high-technology exports) was found to have a significant negative relationship with unemployment, implying that technology-based economic transformation could generate additional employment opportunities when supported by sufficient human capital and economic growth. Overall, the results suggest that the labour-market effects of global automation pressure depend largely on the ability of developing economies to upgrade education systems, workforce skills and sustainable economic growth.

5.2 Implications for Policy

The findings of this study point to some important policy implications for developing economies.

First, governments should boost the investment in education and human capital development to improve workers' adaptability to technological transformation and reduce the risk of technological unemployment. Special focus should be on digital skills, vocational training and lifelong learning programmes that improve competitiveness of the workforce.

Second, policymakers should encourage economic growth strategies that generate productive employment opportunities rather than relying solely on capital-intensive technological expansion. Innovation entrepreneurship and small and medium-sized enterprises can be promoted to absorb labour affected by global automation pressure.

Third, governments should encourage the adoption of technology while simultaneously introducing labour-market adjustment policies. Such policies could include retraining programs, active labor-market interventions and assistance for workers affected by automation-related restructuring to help them transition into new jobs

Finally, by building technological readiness and promoting high-technology industries, developing economies could benefit from technological progress, while minimising labour-market disruptions and improving long-term employment outcomes.

5.3 Recommendations

Based on the empirical results of the study the following recommendations are made:

1. Increase public and private investment in higher education, technical education and workforce training.
2. Design national strategies for digital skills and technological literacy to enhance adaptability in the labour market.
3. Foster innovation and high-technology sectors that can generate sustainable employment opportunities.
4. Develop retraining and reskilling programmes for workers in jobs that are vulnerable to global automation pressure and technological restructuring.
5. Adopt economic policies that promote investment, productivity growth and job creation.
6. Increase cooperation between educational institutions and labour-market stakeholders to ensure that graduates are equipped with skills that are in line with technological developments.
7. Encourage continuous monitoring of labour-market changes in relation to global automation pressure and technological advancement in developing economies.

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