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UNPACKING THE UNEMPLOYMENT PUZZLE IN THE AGE OF ARTIFICIAL INTELLIGENCE: AN ECONOMETRIC PANEL ANALYSIS OF GLOBAL TECH LEADERS

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Abstract
This study focuses on how the impact of Artificial Intelligence (AI)-driven Research & Development (R&D) and the effects of ICT goods exports and ICT goods imports affect unemployment among the top eight high-tech countries by using the data during the years 2010 to 2023 and by employing Driscoll-Kraay standard errors estimation technique, it reveals that there exists a negative significant relationship between the independent variables and the dependent variable that are the AI-led R&D and unemployment, which indicates job creation by productivity. The ICT goods exports also lower unemployment by promoting industries that utilize technology, whereas ICT imports imply employment loss through labor substitution. The results confirm the creative destruction theory, which suggests that strategic investment in innovation and AI has the potential to transform labor markets towards high-skilled jobs.

INTRODUCTION

The twenty-first century is a transformation phase dramatically marked by developments in the field of Artificial Intelligence (AI), an entity that has profoundly transformed human existence and the overall global economy (Acemoglu & Restrepo, 2019). Compared to other waves of technology that focused solely on mechanization and automation, AI is unique in its ability to recreate human-like processes in learning, problem-solving, and decision-making. This capability has attracted unprecedented opportunities as well as challenges for economies worldwide, particularly in terms of labor market dynamics (Autor, 2022). While spurring productivity and innovation, AI has also introduced labor displacement and furthered income inequality (Bessen, 2018). Artificial intelligence is the combination of human cognition in machines, primarily in computer systems, enabling them to perform various tasks, such as learning, reasoning, and problem-solving. It aims to strengthen the ability and systems for any activity that requires intelligent behavior on the part of humans to accomplish the tasks provided. According to Gignac and Szodorai (2024), artificial intelligence has the potential to reduce unemployment by enhancing the efficiency of various processes, fostering innovation, and ultimately driving workforce transformation. With AI automating mundane tasks, human employees will be free to focus on more creative, strategic, and interpersonal tasks, thereby increasing job satisfaction and productivity.

Artificial intelligence has created new job categories in areas such as healthcare, renewable energy, and education, including AI trainers, ethicists, and data specialists, which address skill gaps while enhancing the quality of service delivery (McKinsey, 2017). One of the most highly debated issues surrounding AI adoption is unemployment. Moreover, AI-driven platforms further refashion labor market dynamics by better matching skills with job opportunities, thereby reducing structural unemployment. At the same time, jobs that are difficult to automate, such as those requiring low skills, have remained stable or even increased in demand. These tasks typically require emotional intelligence, human empathy, and complex social interactions, areas where AI technologies remain limited. This has resulted in a polarization of high-skill, low-skill, and middle-skill employment categories as the former two expand while the latter contracts (OECD Employment Outlook, 2022).

Given the already reported concerns about mass job displacement due to artificial intelligence, new research has now shown that AI can reduce unemployment when employed under specific conditions. Technologies induced by AI raise productivity levels, create efficiencies, and open opportunities for workforce reintegration through automation and directing workers to high-value positions (Acemoglu & Restrepo, 2018). Although there is a tremendous amount of literature on unemployment determinants, previous researchers have traditionally focused on economy-wide analysis and have instead emphasized the impact of specific sectors or single-country studies. The productivity of research AI publications that is treated as a one-of-a-kind and fresh indicator provides us with the appropriate tools to consider how technology changes employment structure is yet to be examined within plausible macroeconomic Models; hence, this study will incorporate the prominent big technological tycoons of the advanced world keeping in view the countries which are USA, China, and Japan and seek to see this important study incorporating AI as a new variable in the framework of key factor along with others key indicators. In advanced economies, where the digital economy is growing rapidly, understanding these trends is crucial for formulating policies that encourage inclusive growth. However, the existing literature does not fully integrate AI adoption metrics with broader economic variables, such as ICT trade, demographic shifts, and R&D expenditures. These variables call for a more comprehensive econometric investigation, which this study aims to undertake.

1. LITERATURE REVIEW

The effects of AI differ significantly by industry and skill level. Repetitive and routine jobs have already been mechanized in many fields, like manufacturing, logistics, and administrative work, resulting in dislocation in industries that rely on these types of workers (Frey & Osborne, 2017). With the Artificial infiltration of creative and high-skilled industries, such as finance, healthcare, business, and law, comes new fears of job polarization. High-skilled professionals earn high salaries and exhibit high productivity within countries as AI technology augments their capabilities. In contrast, low-skilled or mid-skilled workers performing tasks based on routines stand a higher chance of being displaced (Arntz et al., 2016).

The emergence of new professions due to AI also has a double-edged sword: while some jobs disappear, others have emerged in fields such as data science, AI ethics, and automation management. The new professions require reform in sectors such as education and workforce training policy to address the evolving needs of AI-based economies. OECD nations have already begun investing in reskilling programs to mitigate the adverse effects of automation, making employees more competitive in the labor market. Such efforts are, however, hindered by the accessibility and responsiveness of schools and training institutions, which in turn impede the preparation of workers with AI-based job skills. A phenomenon commonly known as 'hollowing out' of the middle class, this situation reflects the more and more polarized nature of opportunities for jobs between high-skilled, high-wage jobs and low-skilled, low-wage, dead-end work (Tyson et al., 2022).

Carbonero et al. (2020) examine the global impact of automation, particularly by robots, on the labor market and trade interlinkages. The authors utilize panel data from 2005 to 2014 across various countries to estimate the impact of robot adoption on labor markets. This also generates new employment in advanced, high-tech sectors with complex, sector-specific effects. This is because the more developed countries experience less job-shock intensity due to highly effective reskilling and social safety nets (Abedeen et al., 2024; Ali et al., 2024; Anwar et al., 2024; Shabeer et al., 2024).

Bessen (2015) analyzes the interaction between computer automation job displacement and skill changes in various occupations. The primary variables include automation, job displacement, employment levels, and skill intensity. According to the data from the U.S. economy spanning history, the author analyzes the trends in how industrial and occupational groups adjust to automation over time. The results conclude that automation often leads to the loss of low-skill jobs but simultaneously creates a demand for skilled workers, resulting in a 1.7% increase in employment levels that complements the adoption of new technologies. Hence, this finding contradicts the prevailing view of widespread job losses, as it suggests that most jobs are transformed rather than eliminated, with new roles and skill development resulting from automation (Taymoor et al., 2025; Riaz et al., 2025).

Autor (2013) analyzes the rising polarization of the U.S. labor market and identifies an increase in low-skill service jobs, concurrent with a decline in middle-skill jobs, attributed to technological displacement. The author details how routine middle-skill jobs, such as traditional clerical and manufacturing jobs, are being exploited by automation and computerization, further shrinking the middle-income workforce. Job growth has included both high-skill, high-wage jobs and technical professions on the one hand and low-skill, low-wage service jobs on the other. The structural change pushes many workers into lower-wage sectors, thereby increasing inequality.

Brynjolfsson and McAfee (2014) review how high-velocity technological changes affect labor markets. It spurs productivity growth but also creates job displacements as automated and digital technologies take center stage. The analysis uses economic data from the late 20th century and early 21st century to signal that routine jobs are steadily becoming more susceptible to automation. The main findings suggest that, although technology may open up new avenues, it is likely to exacerbate income inequality, as the disproportionate benefits tend to accrue in favor of high-skilled workers. Their findings emphasize the need for developing effective policy responses to minimize the negative impact of technological displacement on the workforce.

Frey and Osborne (2017) critically examine the impact of automation and AI on future labor markets, estimating that about 47% of jobs are at risk of automation. By utilizing data from the U.S. Bureau of Labor Statistics and other labor market studies, which encompass more than 700 jobs, the authors present an analysis of how the susceptibility of occupations to automation depends on the characteristics of the tasks involved, distinguishing between routine and non-routine tasks. Routine or predictable jobs, such as those in a factory or at any level of administration, will be at the highest risk. At the same time, occupational roles marked by creativity and complex problem-solving are less likely to be affected. Education and retraining programs are recommended to cushion the negative impacts of job displacement. Using the skill-biased and routine-biased theories of technological change, this study emphasizes the urgent need to act proactively in preparing for this change, such as job losses.

2. THEORETICAL FRAMEWORK AND RESEARCH METHODOLOGY

This theory, propounded by Schumpeter (1942), posits that technological change not only destroys old industries but also creates new ones. Disruptive technologies like AI initially destroy jobs by automating routine and semi-routine tasks, resulting in the obsolescence of specific skills. However, historical records indicate that such technology disruptions also create new industries and provide employment opportunities for people. As AI becomes more effective in performing functions that were previously considered exclusive to humans, specific job sectors are becoming obsolete. Routine-based jobs in manufacturing, retail, customer service, and office work have faced severe displacement due to automation.

The Schumpeterian Model of creative destruction explains how innovation (e.g., the adoption of AI) dislocates mature industries and builds new ones, resulting in economic evolution. Here, technological innovations are a form of "creative destruction" that can lead to unemployment; hence, this concept is supported by a strong theory. However, it is also a result of the establishment of new industries and jobs in the long term.

$$Y_t = A_t\,(K_t, L_t)$$

Where:

Y_t: output at time t,

A_t Denotes the technology level or innovation level at time t,

K_t Capital at time t,

L_t Labor at time t,

$F(K_t, L_t)$ is a production function.

$$U_t = \alpha + \beta A_t + \gamma A_t + \delta Z_t + \varepsilon_t$$

In the Schumpeterian framework, the technological level is among the key engines of economic growth, and it also impacts employment. As technology advances, older technologies and professions give way to it, and in the short term, this generates unemployment. In the case of AI and technological change, unemployment can be represented as a function of technological innovation. The Schumpeter model, as used in this paper for the case of AI and job displacement, helps elucidate the interactive dynamics between unemployment and technological advancement (AI adoption).

3.1 Model Specification:

$$Unemp\ rate = \beta_0 + \ln\beta_1\ AI^{*}\ R\&D\ expenditure\ it + \beta_3\ ICT\ goods\ exports + \beta_4\ ICT\ goods\ imports + uit$$

Y= Unemployment rate

$\beta 0$ = the intercept of the Model. It is the constant term of the Model that shows and determines the impact on unemployment when the effect of all other macroeconomic variables is zero

$\beta 1$ = the slope coefficient of AI and R&D expenditure on unemployment.

$\beta 2$ = the slope coefficient of ICT goods exports

$\beta 3$ = the slope coefficient of ICT goods imports

3.2 Summary of Data Sources

Variables, their description, and data sources are given in Table 1.

Table 1
Summary of data sources

Variables	Definition	Source
Unemployment rate	Percentage of the entire labor force that is unemployed and currently seeking work.	WDI
Ln_AI*R&D expenditure	This interaction term variable combines the extent of artificial intelligence (AI) research, represented by the number of AI-related publications, with total research and development expenditure as a percentage of GDP. It shows the alignment between investments in R&D and advancements in AI. The joint variable measures the impact of AI technology-focused innovation on labor dynamics, particularly unemployment.	OECD
ICT goods imports	The percentage of total merchandise imports is made up of information and communication technology (ICT) goods.	WDI
ICT goods exports	The percentage of total merchandise exports is made up of ICT goods.	WDI

3.3 Descriptive Statistics

Details about the variables are given in Table 2.

Table 2
Descriptive Statistics

Variables		Mean	SD	Min	Max
Unemployment rate	Overall	4.906536	1.729574	2.351	9.657
	Between		1.256069	3.319857	6.941929

	Within		1.264315	2.619178	8.614179
ln_ AI*R&Dexp	Overall	1.585565	2.349407	0.136068	5.986933
	Between		1.724449	0.1821507	4.218407
	Within		1.701254	0.037064	4.408264
ICT goods exports	Overall	11.35839	8.654621	1.37	29.18
	Between		9.03146	1.952857	26.29714
	Within		1.699447	4.860536	16.88054
ICT goods imports	Overall	11.76027	4.69302	6.75	24.95
			4.806238	7.312143	21.86214
	1.276677	7.695982		15.78598	

(Author's calculations)

The data pertains to technologically advanced countries, including the United States, China, Japan, Canada, South Korea, Israel, the United Kingdom, and Germany. The descriptive statistics reveal an average level of fluctuation over time between the countries, with a mean of roughly 4.91% and a standard deviation of 1.73. Variations within countries can explain changes in unemployment over time, just as well as variations between countries because the within-country standard deviation (1.26) is slightly lower than the between-country standard deviation (1.26). This suggests a flexible labor market environment where unemployment rates are influenced by both time-related factors, such as policy changes or unexpected economic developments, as well as structural differences between countries. An overall mean of 1.59 and the log of AI-related research expenditures, representing the core explanatory variables, exhibit significant dispersion, reflecting varying levels of AI investment across nations and years. A significant disparity in the adoption of artificial intelligence patterns exists both between and within countries. The import and export volumes of ICT goods also exhibit notable fluctuations: imports have a slightly higher value, while exports show significant differences in trade intensity. For exchange variables, there exists a deviation among countries, which means that the cross-country structural joblessness differences—rather than temporary fluctuations—dominate the nature of trade.

3.4 Estimation technique

3.4.1 Pooled Test Results

Table 3 shows pooled test results

Table 3
Pooled Test Results

Variables	Coefficient	Stand error	T stat	Prob
Constant	2.495629	.8988788	2.78	0.005
ln_ AI*R&Dexp	-0.512862	.0657274	-7.80	0.000
ICT goods exports	-0.104344	.0563409	-1.85	0.064
ICT goods imports	0.374929	.0970656	3.86	0.000

Source: author's calculations

3.4.2 Fixed Effects Results

Table 4 shows fixed-effect results.

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Table 4
Fixed Effects Results

Variables	Coefficient	Stand error	T stat	Prob
Constant	0.341197	.9687917	0.35	0.725
ln_ AI*R&Dexp	-0.55872	.0644808	-8.66	0.000
ICT goods exports	0.036498	0679678	0.54	0.592
ICT goods imports	0.42827	.102366	4.18	0.000

Source: author's calculations

3.4.3 Random Effects Results

Table 5 shows fixed effect results.

Table 5
Random Effects Results

Variables	Coefficient	Stand error	T stat	Prob
Constant	2.495629	.8988788	2.78	0.005
ln_ AI*R&Dexp	-0.512862	.0657274	-7.80	0.000
ICT goods exports	-0.104344	.0563409	-1.85	0.064
ICT goods imports	0.374929	.0970656	3.86	0.000

Source: author's calculations

3.5 Fixed Model v/s Pooled Model

Table 6 shows the Results of the fixed Model v/s the Pooled Model

Table 6
Results of Fixed model v/s Pooled Model

F-Stat(P-value)	5% level of significance
0.0000	0.05

Source: author's calculations

As the value of 0.0000 is less than 0.05, so reject Ho and use the Fixed Effect Model. To choose the test that provides the best estimates, one must make a decision and run some specification tests to distinguish between random and fixed models, thereby obtaining unbiased and efficient estimates. Based on the p-value, a conclusion can be drawn as to whether random is better or not. This is called the Hausman Specification test.

3.5.1 Hausman Specification Test

To choose the test that provides the best estimates, one must make a decision and run some specification tests to distinguish between random and fixed models, thereby obtaining unbiased and efficient estimates. Based on the p-value, a conclusion can be drawn as to whether random is better or not. This is called the Hausman Specification test.

H0: There is a Random Effect
H1: There is a Fixed Effect
Table 7 shows the Hausman Specification Test Results.

Table 7
Hausman Specification Test Results

Chi-Square value	5% level of significance
0.0040	0.05

Source: author's calculations
0.0040 is less than 0.05, so reject Ho and conclude that the fixed effect model is preferred

3.6 Post Estimation test

3.6.1 Pesaran CD Test For Cross-Sectional Dependence

H0: There is weak cross-sectional dependence in the Model.
H1: There is strong sectional dependence in the Model.
Table 8 shows the Results of the Pesaran CD Test for cross-sectional dependence

Table 8
Results of the Pesaran CD Test For Cross-Sectional Dependence

Chi-sq	5% level of significance
0.019	0.05

As the CD value is less than 0.05, we fail to reject the null hypothesis and conclude that there is strong cross-sectional dependence in the Model.

3.6.2 Wald test for heteroscedasticity

H0: There is no heteroscedasticity in the Model.
H1: There is heteroscedasticity in the Model.
Table 9 shows the Results of the Wald Test For Heteroscedasticity.

Table 9
Results of the Wald Test For Heteroscedasticity

Chi-sq	5% level of significance
0.001	0.05

Source: author's calculations
As the p-value is 0.001 < 0.05, so reject Ho and conclude that there is a problem of heteroscedasticity in the Model.

3.6.3 Wooldridge test for serial correlation

H0: There is no serial correlation in the Model.
H1: There is a serial correlation in the Model.
Table 10 shows the Wooldridge Test for Serial Correlation.

Table 10
Wooldridge Test for Serial Correlation

Chi-sq	5% level of significance
0.000	0.05

Source: author's calculations
As the p-value is 0.000 < 0.05, we reject H0 and conclude that there is a problem with serial correlation in the Model.

3.6.4 Multicollinearity test:

Table 11 shows the Results Of the Multicollinearity Test

Table 11
Results Of the Multicollinearity Test

Mean VIF
3.7

Source: own calculation by the author.
As VIF is 3.7, which is less than 10, there is no multicollinearity among the independent variables in the Model

3.6.5 Driscoll Kray Standard Errors:
It is one of the most authentic methods because it corrects for cross-sectional dependence, serial correlation, and heteroscedasticity in the Model. Table 12 shows Driscoll-Kray Standard Errors.

Table 12
Results of Panel Corrected Standard Errors

Variables	Coefficient	Stand error	T stat	Prob
Constant	4.08452	.23708	17.23	0.000
ln_ AI*R&Dexp	-0.45165	.0398371	-11.34	0.000
ICT goods exports	-0.19892	.0397238	-5.01	0.000
ICT goods imports	0.322913	0427597	7.55	0.000

Source: own calculation by the author.

4 DISCUSSIONS
Different diagnostic tests indicate that the Driscoll-Kray Standard Error provides the most statistically reliable estimates. First, it has been indicated that heteroscedasticity is present, meaning error variances differ across countries, thereby violating the assumption of homoscedasticity. This would lead to inefficient standard errors if not corrected, potentially overstating or understating the effect of AI and R&D expenditure on unemployment levels in these technologically advanced nations. Secondly, the Pesaran CD test detects cross-section dependence. To do so, it would introduce errors between countries, causing spurious statistical significance for explanatory variables. Thirdly, the Wooldridge test detects a first-order autocorrelation. This persistence, which is common in labor market studies, if left unaddressed, would result in an inefficient parameter estimate. Driscoll and Kray SE, in contrast to other models, solve all three econometric issues directly and are, therefore, the best estimation approach to adopt in this study (Driscoll & Kraay, 1998). This Model's estimation confirms the association between AI and R&D expenditure collectively and unemployment, a fact that has been argued so vigorously by economists. Low-skilled workers are replaced by the adoption of AI and R&D expenditure, leading to an increase in joblessness. However, as economies adjust by creating new jobs, upgrading skills, and incorporating AI into productive industries, joblessness decreases. According to Driscoll Kray SE, the estimated coefficients are economically significant (Bordot, 2022).
Diagnostic tests highlight the dependability of the Model. The Modified Wald test demonstrates heteroskedasticity across nations. The Wooldridge test validates the existence of serial correlation, supporting the use of Driscoll-Kraay robust standard errors, which correct for these three core issues: cross-sectional dependence, Serial correlation, and heteroskedasticity. At the same time, the final Model's R-squared value (~44%) collectively indicates the goodness of fit. These findings highlight that while ICT trade dynamics have more complicated effects on the labor market, AI-driven R&D plays a significant role in minimizing unemployment in industrialized nations.
The data collected suggest a strong, negative, and significant association between the unemployment rate in each of the eight high-tech nations and the amount spent on AI research and development (logged). An interaction term has been used to assess

its impact on the unemployment rate. A 1% increase in AI R&D spending is consistently linked to a 0.5% drop in unemployment, according to both the fixed-effects and random-effects models. This suggests that increased AI innovation decreases job losses as a result of increased productivity, the spread of new technologies, and the creation of new job market opportunities. Estimates are validated by the Hausman test, which favors the use of fixed effects. Conversely, ICT goods exports exhibit varying coefficient signs, yet an insignificant relationship with unemployment in FE and RE; however, this relationship becomes highly significant in the Driscoll-Kraay SE model. Conversely, ICT product imports consistently display a positive and statistically significant coefficient, indicating a correlation between increased ICT product imports and higher unemployment. This might indicate structural adjustment issues with the environment or substitution effects, where domestic labor is replaced by imported technology.

The interaction term ln_ai_rdexp (log of expenditures for AI-related R&D) possesses a markedly significant and negative coefficient (β = -0.4517, $p < 0.01$), suggesting that a 1% increase in AI-related R&D reduces unemployment by -0.45165%. This finding supports the complementarity hypothesis in innovation economics, suggesting that AI-driven R&D enhances labor productivity and fosters the development of new tasks, roles, and industries (Acemoglu & Restrepo, 2019). Within the framework of endogenous growth theory (Romer, 1990), this investment fueled by innovation serves as a productivity enhancer, capable of counteracting job-displacing automation by creating new demand and jobs in knowledge-intensive sectors. Additionally, AI technology enhances productivity, drives new employment creation, and sparks complementary job growth. Although AI-fueled R&D-driven automation may replace some jobs in the short term, effective reskilling and policy action can ensure that technology leads to employment increases (Wang et al., 2021). The shift towards knowledge-based economies from the traditional sectors has caused the demand for labor to change in favor of individuals with advanced education and computer skills. The result supports Schumpeter's creative destruction hypothesis, which posits that technological advances destroy existing economic institutions but ultimately lead to long-term employment gains through industrial transformation. Empirical evidence also supports this claim, showing that more stable AI R&D expenditures lead to greater job growth, specifically in the information technology, biotechnology, and automation sectors.

Moreover, the negative and notable impact of ICT goods exports on joblessness (β = -0.1989, $p < 0.01$) suggests that a 1% increase in ICT goods exports results in a 0.1989% decrease in unemployment rates. This can be understood through the export-oriented job creation framework (Helpman & Krugman, 1985), where involvement in ICT production and exports. The exportation of ICT goods reflects a country's capacity to create in cutting-edge tech sectors, where investments in AI and research and development can be fostered and enhanced. As a result, the adverse signal strengthens a positive loop where AI-fueled innovation gives rise to enhanced production, which further boosts ICT exports, leading to higher job creation, especially in skilled sectors of the labor market. An increase in ICT exports significantly increases employment by generating technologically sophisticated industries, raising global competitiveness, and leading to industrial diversification. Typical ICT goods-exporting countries often have well-developed digital economies, sophisticated R&D capabilities, and high-quality labor markets, which all result in declining rates of unemployment (OECD, 2022).

On the other hand, the positive and statistically significant coefficient for ICT goods imports (β = 0.3229, $p < 0.01$) implies that a 1% increase in ICT goods imports leads to a 0.3229% in the unemployment rate and a potential labor-displacement effect when economies rely on importing advanced technologies instead of developing them domestically. This aligns with the capital-labor substitution theory (Acemoglu & Autor, 2011), as foreign digital technologies automate routine or lower-skilled positions, leading to higher unemployment if labor markets fail to adjust. In contrast to ICT exports, which signify local manufacturing and jobs, ICT imports may indicate the consumption of international innovations, potentially displacing local workers if there are no supportive AI policies or adaptive skill frameworks in place. Consequently, policy implications suggest aligning technology imports with domestic AI research and development capabilities, as well as the strength of the labor market. In conclusion, the findings support a story: AI-enhanced R&D and advanced technology exports lower unemployment, whereas excessive dependence on foreign tech imports without building local capabilities may worsen it.

5 CONCLUSIONS

This research demonstrates that when AI-driven R&D is effectively integrated with local innovation systems, it significantly reduces unemployment in advanced economies, using data from the countries of the UK, USA, China, Canada, Korea, Israel, Germany, and Japan for the period from 2010 to 2023. Using the Driscoll-Kraay estimation method—confirmed by diagnostic assessments for heteroskedasticity, cross-sectional dependence, and serial correlation—guarantees strong statistical reliability. The independent variable, reflecting the degree of AI and R&D, consistently demonstrates a significant negative correlation with unemployment, reinforcing theories of growth fueled by innovation and the concept of creative destruction. Exports of ICT goods promote job growth by enhancing technological competitiveness and industrial diversity, thereby fostering a more robust economy. In contrast, the increase in ICT imports is associated with higher unemployment, likely because automation leads to job losses. These results highlight the necessity for fair technological approaches: promoting domestic AI development and advanced technology exports while carefully regulating imports through skills improvement and industry policies. Overall, the findings suggest that AI-focused innovation ecosystems can facilitate changes in employment, provided that policy structures promote local skill enhancement and inclusive technology integration.

6 POLICY RECOMMENDATIONS

- Governments should increase funding to invest in AI and research and development, thereby spurring innovation-driven job growth. Public-private partnerships and university collaborations can accelerate the pace of technology. It raises productivity and creates local high-skilled employment opportunities.
- Support ICT-exporting industries with targeted incentives and infrastructure development. This goes hand in hand with developing digital skills training aligned to export industries. This ensures that export growth translates into sustainable and inclusive employment opportunities.
- Implement strategic ICT import regulations to avoid over-reliance on foreign automation. Integrate technological progress with workforce reskilling and upgrading AI absorption capacities. This minimizes job loss and enables easier transitions in the labor market.

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