Scientific Annals of Economics and Business
72 (2), 2025, 1-19
DOI: 10.47743/saeb-2025-0021

AI-Driven Transformation in Employment and Labor Income: A Global Analysis of Workforce Dynamics

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Abstract: Artificial intelligence (AI) technology has profoundly transformed the landscape of work, exerting substantial influence on employment and labor income dynamics. This study leverages global AI index data to investigate the implications of AI adoption on employment rates and labor income shares. The findings reveal a detrimental effect of AI on both employment opportunities and the proportion of income allocated to labor, with these impacts varying significantly among different worker demographics and across various countries. By unpacking the current effects of AI technology on the labor market, this paper provides valuable insights and potential strategies to address and mitigate the adverse outcomes associated with the integration of AI in the workforce.

Keywords: artificial intelligence; employment; labor income share.

JEL classification: F01; J21; J31.

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Article history: Received 15 December 2024 | Accepted 8 April 2025 | Published online 18 June 2025

To cite this article: Gao, Y. (2025). AI-Driven Transformation in Employment and Labor Income: A Global Analysis of Workforce Dynamics. *Scientific Annals of Economics and Business*, 72(2), 1-19. https://doi.org/10.47743/saeb-2025-0021.

1. INTRODUCTION

Artificial Intelligence (AI), a term first used by John McCarthy in 1955 at the Dartmouth Conference, refers to the field of creating intelligent machines. It can be broadly categorized into Narrow AI, which excels in specific tasks, and General AI, which possesses a broader cognitive ability (Poole and Mackworth, 2010)[1,2]. Advances in machine learning and deep learning have led to AI systems that improve autonomously, recognize patterns, and make decisions using large datasets and complex algorithms (Goodfellow *et al.*, 2016). Today, AI is widely understood as intelligent systems or machines capable of understanding, learning, reasoning, perceiving, and making decisions (Russell and Norvig, 2020), drawing inspiration from and simulating aspects of human cognitive processes.

This transformative technology has seamlessly integrated into our daily lives, revolutionizing sectors such as transportation, customer service, finance, and healthcare. Innovations like self-driving cars, automated customer service bots, and sophisticated financial analytics are now part of our reality. The launch of ChatGPT-3.5 by OpenAI in November 2022 marked a significant milestone in natural language processing, significantly enhancing human-computer interactions and further expanding the potential of AI applications.

Economically, the impact of AI is expanding rapidly, reflecting its growing importance and influence. Investment in generative AI surged in 2023, reaching $25.2 billion, nearly eight times the previous year's investment (Perrault and Clark, 2024), underscoring the significant financial stakes associated with AI development. This economic shift is not limited to traditional tech sectors; AI is transforming work and production across various industries, leading to significant changes in employment and income distribution.

Unlike previous automation waves, AI's impact extends beyond routine tasks, leveraging continuous learning to improve predictions and recommendations. This shift has profound implications for the job market, posing threats to high-skilled jobs such as stock analysts and lawyers, previously considered immune to automation. The World Economic Forum predicts that digitization and automation could displace 26 million jobs by 2027 but also create 4 million new digital roles, raising concerns about job market stability. The rise of AI is also reshaping income distribution, fueling demand for experts in AI engineering, data science, and machine learning, while traditional low-skilled jobs face falling wages and fewer opportunities, potentially widening the income gap.

Understanding the effects of AI on employment and income is crucial for navigating the challenges and opportunities presented by this technological transformation. By examining these impacts, insights can be gained into the potential societal and economic implications of AI and recommendations can be provided for policymakers to foster sustainable economic development and ensure that individuals can benefit from the AI era.

This paper contributes to the ongoing discourse on AI's economic impact by leveraging the Global AI Index, a standardized indicator that has not been utilized in previous research to conduct a comprehensive global analysis of AI's influence on employment rates and labor income shares. Additionally, the paper demonstrates that the specific impact of AI on employment varies depending on individual and national characteristics, providing a nuanced understanding of AI's multifaceted effects on the global economy and society.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature and outlines research hypotheses. Section 3 describes data selection and empirical strategies employed. Section 4 presents empirical results, followed by a conclusion and recommendations in Section 5.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 The dual impact of AI on employment

The impact of AI on employment remains a subject of debate, primarily due to the interplay between the substitution effect and the creation effect. According to the substitution effect, AI causes job displacement through "machine substitution," potentially reducing employment opportunities. The creation impact, on the other hand, claims that the adoption of AI engenders the emergence of new job opportunities, increases labor productivity, fosters the creation of new occupations, and contributes to the overall enhancement of employment levels.

AI diminishes labor demand via the substitution effect. Technological progress leads to the replacement of labor with capital, particularly in industries where AI excels at repetitive tasks through robotics. This shift results in technological unemployment, as companies opt for robots to enhance efficiency and lower costs, displacing workers (Acemoglu and Restrepo, 2020c). Internationally, Frey and Osborne (2017) estimate that nearly half of U.S. occupations are at risk from AI, with a higher replacement rate of 77% in China. In China's manufacturing sector, Yan *et al.* (2020) found that a 1% increase in industrial robot usage corresponds to a 4.6% monthly decline in jobs. Wang and Dong (2020) further substantiate these findings, highlighting a predominant substitution effect over job creation.

Moreover, the impact of AI on the labor market extends beyond straightforward job displacement. The rise of AI has increased the demand for technical skills and continuous learning from workers, leading to a discrepancy between existing skills and job requirements. This mismatch has the potential to result in structural unemployment (Acemoglu and Restrepo, 2018). Unlike previous technological advancements, AI can simulate human behavior in more sophisticated ways using big data and machine learning, thereby amplifying its potential to replace human labor. In particular, the advent of generative AI, exemplified by ChatGPT, puts jobs that involve mental tasks such as data analysis, information retrieval, and content generation at risk of displacement. Research by Cai and Chen (2019) shows that the integration of AI in China has intensified the challenge of aligning job structures with the age composition of the workforce. This issue is more pronounced when overall educational attainment is low, which could lead to significant concerns about structural unemployment in the short to medium term.

Conversely, AI boosts labor demand through its creation effects. Firstly, AI adoption fosters the development of new products and services, generating new jobs and expanding employment (Barro and Davenport, 2019; Raisch and Krakowski, 2021). In manufacturing, robot deployment has led to roles in maintenance and AI development. AI's integration in sectors like finance, healthcare, and education has also spawned new professions, such as data scientists and AI specialists, enriching labor market diversity. U.S. data confirms that AI adoption has led to new tasks and occupations (Acemoglu *et al.*, 2022; Autor *et al.*, 2024). Similarly, Chinese manufacturing data indicates a positive long-term job impact from robot use (Wang *et al.*, 2022b). Secondly, AI enhances production efficiency, boosting supply and stimulating demand, which in turn increases employment (Trajtenberg, 2018). Graetz and Michaels (2018) show that robot use raises labor productivity and total factor productivity, lowering output prices. Studies by Autor and Salomons (2017) and Gregory *et al.* (2016) suggest that productivity gains drive up consumption, income, and employment. Thus, the creation effect partially offsets the substitution effect of AI, contributing to employment stability.

In essence, the overall effect of AI on employment hinges on the balance between substitution and creation effects, with current opinions divided. Some research suggests AI's employment impact could be neutral, forecasting stable total employment in the future (Cai and Chen, 2019). As Dauth *et al.* (2017) showed with German data, robot adoption does not necessarily lead to job losses, as manufacturing declines are counterbalanced by service sector gains. Current empirical studies on the impact of AI on employment mostly focus on single-country cases, which makes it difficult to reflect cross-border differences and global structural impacts. However, the latest research based on global data shows that AI has a negative impact on the job market (Georgieff and Hyee, 2022; Hui *et al.*, 2024). Thus, the hypothesis is proposed:

***H1**: The adoption of AI technology has a net negative effect on employment rates.*

2.2 AI's role in shaping job structures and employment dynamics

The debate over AI's impact on employment volume persists, yet its potential to reshape job structures is universally recognized. The nuanced influence of AI on labor markets is evident through the interplay of worker skills, education, job types, and the varying levels of economic development and AI adoption across countries.

AI's influence on the workforce is closely tied to skills, education, and job types. It has led to employment polarization, with a rise in demand for both high- and low-skilled jobs at the expense of middle-skilled positions (Felten *et al.*, 2019; Sholler and MacInnes, 2024). Non-routine tasks, often complex or adaptable, are less susceptible to AI, while standardized, automatable middle-skilled jobs are more at risk (Lassébie and Quintini, 2022). This trend is supported by data from the U.S., EU, and China (Autor and Dorn, 2013; Autor, 2015; Sun and Hou, 2019). However, the effect on low-skilled labor is unclear, with some studies showing a decline in employment due to robotics in manufacturing (Graetz and Michaels, 2018; Xie *et al.*, 2021).

Education level correlates with job vulnerability to AI. Higher education generally means higher skills and non-routine work, making less educated workers more at risk of replacement, especially in routine roles (Autor *et al.*, 2003; Zhou *et al.*, 2020). Those with lower qualifications, particularly bachelor's degrees or less, face the toughest challenges in adapting to AI (Wang and Dong, 2020). Bughin *et al.* (2018) predict a decrease in jobs involving repetitive, low-digital-skill tasks from 40% to 30% by 2030.

AI's effect on employment varies with a country's economic development, industrial composition, and AI adoption level. AI has widened the employment gap between developed and developing regions, known as spatial employment polarization. AI challenges the traditional growth model in developing areas, diminishing their labor-cost advantage in attracting investment (Cheng and Peng, 2018). Developed countries may experience a manufacturing revival, risking deindustrialization in developing economies (Hui, 2020). Within the manufacturing sector, AI has a profound impact on employment (Cao and Xu, 2020). The industry's reliance on repetitive labor makes it ripe for AI-driven automation, leading to job displacement and the creation of new, technically demanding roles. Additionally, the impact of AI on employment is phased, with leading regions in AI adoption experiencing industry clustering that draws talent and services (Wang *et al.*, 2017). In contrast, regions that lag in AI industry-related innovation may suffer labor outflow due to a lack of investment and development opportunities. Given the diverse factors at play, the hypothesis is formulated as follows:

H2: *Variations in individual (education attainment) and national characteristics (economic development, industrial composition, AI adoption intensity) affect the employment impact of AI.*

2.3 AI's role in shaping job structures and employment dynamics

The evolution of the employment structure is paralleled by shifts in income distribution, heightening concerns about income inequality (Acemoglu and Autor, 2012). The impact of AI on income distribution is pronounced in its effect on the labor income share. The adoption of AI in production has increased capital's share, widening the wage gap between labor and capital (Ernst *et al.*, 2019). Since the 1980s, a notable decline in the labor income share across various countries and sectors has been attributed to the spread of information and computer technologies, prompting a shift towards capital-intensive production methods (Karabarbounis and Neiman, 2014).

AI alters income distribution by reshaping the workforce structure. One perspective is that AI-driven employment polarization reduces low-skilled job opportunities, leading to increased competition and lower wages for these workers. In contrast, the scarcity of high-skilled labor drives up their wages, widening the wage gap between high- and low-skilled workers (Autor and Salomons, 2017). Studies across countries support this pattern. Acemoglu and Autor (2011) found that the income gap between educated and less-educated Americans has widened since 1980. Dauth *et al.* (2017) noted that industrial robots in Germany reduced middle-skilled wages while increasing those of high-skilled managers. Wang *et al.* (2020) observed a similar trend in China, with AI contributing to an annual 0.75% increase in the income gap between high- and low-skilled labor. Another viewpoint is that AI exacerbates skill disparities, enhancing productivity for high-skilled workers and contributing to the widening income gap (Korinek and Stiglitz, 2018). Over time, this trend could indirectly benefit capital owners and deepen social class divisions (Acemoglu and Restrepo, 2020c). The hypothesis is:

H3: *The use of AI reduces the labor income share, exacerbating income inequality between labor and other economic agents.*

In summary, existing literature has extensively examined AI's impact on employment, centering on job numbers, employment structures, and income distribution. These studies offer valuable insights and analytical tools. However, empirical research predominantly focuses on the micro level and lacks sufficient macro-level analysis, such as AI's influence on economic development across countries. Additionally, macro-level studies are biased towards developed nations and China, neglecting a broader, comparative approach across various regions. This oversight calls for research on the commonalities and differences in AI's employment effects across countries, which is essential for informing national strategies and policies.

3. DATA SELECTION AND RESEARCH DESIGN

3.1 Data selection

This study undertakes a comprehensive analysis of the impact of AI on employment and labor income share by using data from a diverse range of sources. The data spans 45 countries over the period from 2000 to 2022, offering a broad perspective on the influence of AI in different economic and social contexts, examining factors such as educational level, AI development, industrial disparities, and stages of economic growth (*H2*). This 22-year timeframe is pivotal in the narrative of AI, commencing amidst the AI winter of 2000, traversing the renaissance circa 2010, and peaking with the introduction of the AI landmark, ChatGPT, in 2022. This era shows AI's transformative trajectory, marked by progressive evolution and exponential breakthroughs. All the data used in this study are annual data.

Dependent Variables: The employment level is measured by the employment rate of the population over 15 years old (*employ*). This variable is sourced from the International Labor Organization database. It serves as a crucial indicator to assess how adoption of AI affects the proportion of the working-age population that is gainfully employed. The labor income share (*labor_share*) is calculated as the labor income as a percentage of GDP. This metric, which captures the distribution of economic output between labor and capital, is obtained from the World Bank database.

Independent Variable: The primary explanatory variable is the AI level (*AI*), which reflects the degree of AI adoption in each country. Conventionally, studies measure AI levels using data on industrial robots from the International Federation of Robotics (IFR) and AI patent counts. However, these methods are not without their shortcomings. IFR data, being industry-specific, overlooks sectors such as healthcare. Moreover, it defines industrial robots narrowly as multi-jointed machines for production automation, failing to encapsulate the full breadth of AI. Additionally, data delays limit a comprehensive view of the global robot market. AI patent data is also subject to delays, incomplete coverage, inconsistent international standards, and the risk of double counting. In this analysis, the Global AI Index by AI Rankings is utilized instead[3]. This index evaluates AI across six critical domains: computer vision, natural language processing, machine learning, cognitive reasoning, robotics, and multi-agent systems. The AI Index provides a more holistic and interdisciplinary evaluation by computing the geometric means of pertinent publications, which mirrors global AI research capabilities. It is an objective, extensive measure that enables meaningful international comparisons.

Control Variables: Drawing on studies by Jiang *et al.* (2023), Wang *et al.* (2022a) and Wang *et al.* (2023), several control variables are incorporated to account for factors influencing employment and labor income share. Economic development is represented by the logarithm of GDP per capita (*ln gdp*), sourced from the World Bank database. Population size, measured as the logarithm of the total population (*ln population)*, also comes from the World Bank. Educational attainment, indicated by the logarithm of average years of education (*ln school*), is obtained from the Global Data Lab database. The proportion of the population aged 65 and older (*aging*), reflecting the level of aging, the proportion of value added by the secondary industry in GDP (*indu*) for industrial structure, and the proportion of the urban population in the total population (*urban*) for urbanization level are all sourced from the World Bank. The cost of living, represented by the Consumer Price Index with 2010 as the base year (*cpi*), is from the Global Data Lab database. The degree of international trade, measured by the share of the value of imports and exports of goods and services in GDP (*open*), is sourced from the World Bank.

For detailed information of the data see Annex. Table no. 1 provides a comprehensive overview of the descriptive statistics for each variable.

Table no. 1 – Descriptive statistics

Variable	Observations	Mean	Standard deviation	Min	Max
employ	1035	56.805	8.933	34.995	88.206
labor_share	765	51.759	10.374	14.93	68.43
AI	889	9.37	30.785	0	342.54
ln gdp	1034	10.32	0.805	7.726	11.701
ln population	1035	16.879	1.791	12.874	21.072
ln school	963	2.318	.282	1.19	2.648
aging	1035	12.667	6.169	0.172	29.925
indu	1014	27.106	10.15	2.759	73.469
urban	1035	75.319	17.252	23.59	100
cpi	995	107.036	52.604	20.595	1031.658
open	1027	94.026	72.515	19.56	437.327

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). *employ* (employment rate of the population over 15 years old). *labor_share* (labor income as a percentage of GDP). *AI* (Global AI Index). For the control variables: *ln_gdp* (logarithm of GDP per capita), *ln_population* (logarithm of total population), *ln_school* (logarithm of average years of education), *aging* (proportion of population aged 65 and older), *indu* (proportion of value added by the secondary industry in GDP), *urban* (proportion of urban population in total population), *cpi* (Consumer Price Index with 2010 as the base year), and *open* (share of value of imports and exports of goods and services in GDP).

3.2 Research design

Model (1) and Model (2) were established as baseline models to evaluate the influence of AI on employment (*H1*) and labor income share (*H3*).

$$\text{employ}_{it}=\alpha_0+\alpha_1\times \text{AI}_{it}+\text{A}\times \text{X}_{it}+\mu_i+\xi_t+\varepsilon_{it} \quad (1)$$

$$\text{labor\_share}_{it}=\beta_0+\beta_1\times \text{AI}_{it}+\text{B}\times \text{X}_{it}+\mu_i+\xi_t+\varepsilon_{it} \quad (1)$$

where subscripts i and t represent the country and year respectively, μ_i and ξ_t respectively represent the country fixed effect and year fixed effect, and ε_{it} is the error term, using robust standard errors. $employ$ indicates the employment level, $labor\_share$ represents the labor income share. AI serves as the primary explanatory variable. The variable set X includes control variables (*ln gdp*, *ln population, ln school, aging, indu, urban, cpi, open*).

4. EMPIRICAL RESULTS

4.1 Baseline results

Columns (1) and (2) of Table no. 2 present the findings from the stepwise regression analysis applied to the baseline regression Model (1). Column (1) restricts the analysis to year and country fixed effects. Expanding the scope, Column (2) incorporates a range of national characteristics, including the level of economic development, population size, educational attainment, aging demographics, industrial composition, urbanization rates, cost of living, and the extent of international trade.

The results are statistically significant at the 1% level, revealing a pronounced association between the advancement of AI and employment rates. Specifically, for each unit improvement in AI capabilities, the employment rate experiences a decrease of 0.018% in Column (1) and 0.014% in Column (2). This indicates that even after accounting for country-specific traits and year and country fixed effects, the proliferation of AI exerts a noticeable dampening effect on employment levels, in support of H1.

Columns (3) and (4) of Table no. 2 elaborate on the outcomes for the baseline regression Model (2), which also employs the stepwise regression method. These results underscore AI's adverse influence on the labor income share. With every unit increase in AI's strength, the labor income share diminishes by 0.016% and 0.012% respectively, suggesting a widening income gap between labor and other economic agents. This pattern highlights the potential for AI to exacerbate income disparities between labor and other economic agents, in support of H3.

Table no. 2 – Baseline results

Variable	**employ**		**labor_share**	
	(1)	(2)	(3)	(4)
AI	-0.018***	-0.014***	-0.016***	-0.012***
	(-4.178)	(-3.810)	(-4.000)	(-3.123)
Control variable	No	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	889	795	673	636

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex).The first two columns present the results of Model (1) and the last two columns show the results of Model (2). The coefficients are obtained from the stepwise regression analysis of the baseline regression models. In column (1) control for country and time fixed effects and in column (2) add control variables mentioned in Section 3.1. The same as column (3) and (4). The values in parentheses are robust standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The following tables are the same.

4.2 Endogeneity problems

The COVID-19 pandemic has undoubtedly impacted both the progression of AI technology and employment rates from 2020 to 2022. This presents a risk of endogeneity bias due to common determinants. To address this issue, we exclude the data from 2020 to 2022 from our regression analysis. The results in columns (1) and (2) of Table no. 3 demonstrate that even after removing this period, a significant negative correlation persists between AI advancement and employment rates, with coefficients of -0.017 and -0.013, respectively. This reinforces the stability of our baseline findings.

Conversely, reverse causality is a consideration: shifts in labor's income share could potentially influence a country's AI development. Typically, a higher labor income share suggests more funding available for AI research and development, thereby enhancing AI capabilities. To tackle this, we adopt the methodology proposed by Acemoglu and Restrepo (2020a), utilizing the AI levels of countries with comparable income levels as an instrumental variable (IV). Firstly, the AI level of peer countries in terms of income can serve as a reasonable proxy for a given country's AI standing, fulfilling the relevance condition. Secondly, this AI level is independent of the country's labor income distribution, satisfying the exclusivity condition. Considering the significant AI disparities across geographic regions (ANOVA test P-value< 0.000), we use the average AI level of countries with similar income levels within the same region as our IV. Specifically:

Geographic Regions: Countries are first grouped into 4 World Bank geographic regions (AM, AS, AU, EU).

Income Grouping: Within each region, countries are further classified into four income quartiles based on logarithm of GDP per capita (constant 2017 international USD) from the World Bank WDI.

Columns (3) and (4) of Table no. 3 show that the coefficient for this IV is significantly positive at the 1% significance level. Moreover, the F statistic exceeds its critical value, alleviating concerns about weak instruments. In the second stage of the analysis, the regression result for the IV is notably negative (-0.00946) at the 10% significance level, further solidifying the robustness of the baseline results.

Table no. 3 – Endogeneity test

Variable	employ		AI	labor_share
	(1)	(2)	(3)	(4)
AI	-0.017*** (-3.931)	-0.013*** (-3.556)		-0.00946* (-2.55)
IV			0.980*** (173.94)	
Control variable	No	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	764	717	626	626
F-statistic			30256.7	

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). In the first two columns related to employment (employ), the coefficients for the AI variable are obtained from regression analysis after excluding the data from 2020-2022. The calculation of these coefficients follows the same regression procedures as in Table no. 2. For the instrumental variable (IV) analysis in columns (3) and (4), the coefficient of the IV is estimated through a two-stage least square (2SLS) regression. In the first stage, the AI level of the country regressed on the IV and control variables mentioned in Section 3.1. In the second stage, the labor income share is regressed on the predicted AI level from the first stage and the control variables mentioned in Section 3.1.

4.3 Robustness test

(1) Change core explanatory variables

Considering the potential time lag in the employment effects of AI technology as measured by the AI index, the AI index from the previous year is used for robustness checks. The results in columns (1) and (2) of Table no. 4 continue to align with the baseline results.

AI Index represents scientific research in the AI field and not the integration of AI into daily operations performed by the workforce, I utilize the industrial robots stock data of IFR, which directly measures automation in manufacturing operations. This choice aligns with prior literature (Acemoglu and Restrepo, 2020a) that identifies robot density as a key proxy for workplace automation implementation. As shown in Table no. 4, columns (3)-(4), the coefficients for robot stock (-0.000008***, -0.000009***) maintain statistical significance and directionality consistent with the baseline results. This confirms that the negative employment effect persists across different operationalizations of AI adoption, whether measured through research capabilities or industrial deployment metrics.

(2) Poisson regression

Considering that $employ$ and $labor\_share$ does not perfectly follow the normal distribution, a panel Poisson regression model was utilized, controlling for year-fixed effects and country-fixed effects. The results in columns (5) and (6) of Table no. 4 remain consistent with the baseline findings.

Table no. 4 – Robustness check

Variable	employ	labor_share	employ	labor_share	employ	labor_share
	(1)	(2)	(3)	(4)	(5)	(6)
AI	-0.013***	-0.019***			-0.000239***	-0.000204***
	(-3.532)	(-4.135)			(-4.0)	(-3.1)
Robots stock			-0.000008***	-0.000009***		
			(-4.1)	(-3.9)		
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	876	716	713	573	795	636

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, World Bank database and International Federation of Robotics (for detailed information refer to Annex).In terms of replacing the core explanatory variable, the columns (1) and (2) conduct regression analyses using the AI Index of the previous year, while the columns (3) and (4) perform regression analyses using the Robots stock of the IRF. In columns (5) and (6), the coefficients are estimated using the Poisson regression technique. Control variables are the control variables mentioned in Section 3.1.

4.4 Heterogeneity analysis

(1) Heterogeneity analysis based on individual characteristics

AI, characterized by its self-learning abilities, presents a unique model of labor displacement distinct from previous technological breakthroughs. The impact of AI on high-skilled versus low-skilled labor varies markedly. For high-skilled labor, AI holds the potential to displace jobs involving cognitive tasks, yet simultaneously generates new employment opportunities and boosts the demand for skilled workers. In contrast, low- and medium-skilled labor is more susceptible to the substitution effects of AI, especially in roles involving routine tasks, while the automation of non-routine tasks remains a more formidable challenge. Consequently, an in-depth examination is undertaken to understand how AI influences employment rates across different skill levels within the labor force.

Educational attainment is frequently regarded as a credible proxy for employee skill levels (see Acemoglu and Restrepo, 2020b). In light of this, the heterogeneity analysis employs the employment rate among individuals with different educational qualifications as the dependent variable, thereby capturing the labor force's employment status across various skill strata. Table no. 5 presents the differential effects of AI on employment rates within the labor force stratified by educational background. The results indicate a statistically significant negative impact of AI on the employment rates of individuals with higher and secondary education levels at the 1% significance level, with respective coefficients of -0.019 and -0.016.

Conversely, a significant positive effect is observed on the employment rate of those possessing only a basic education (0.019), while no significant effect is detected on the employment rate of individuals with an education below the basic level. This suggests that AI exerts a differentiated influence on the employment of high- versus low-skilled labor. The technology's capability to perform certain cognitive and routine tasks through self-learning is evident. However, the negligible impact on the employment rate of low-skilled labor may correspond to the intrinsic challenges associated with automating jobs that require manual dexterity and physical labor.

Table no. 5 – Individual heterogeneity

Variable	employ			
	Advanced (1)	**Secondary** (2)	**Basic** (3)	**Less than basic** (4)
AI	-0.019*** (-4.907)	-0.016*** (-3.190)	0.019*** (4.186)	-0.003 (-0.345)
Control variable	Yes	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	613	615	607	443

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). The coefficients are derived from regression models, controlling for year and country fixed effects as well as control variables mentioned in Section 3.1, where the dependent variable is the employment rate among individuals with different educational qualifications (advanced, secondary, basic, and less than basic).

(2) Heterogeneity analysis based on country attributes

Prior research has logically posited that the effects of AI on employment vary across stages of economic development (Cheng and Peng, 2018) and among industries (Cao and Xu, 2020), exhibiting stage-specific characteristics (Wang *et al.*, 2017). However, these studies lack data validation. Recognizing the disparities in AI's impact on employment due to country heterogeneity, this study investigates the manner in which AI influences employment across different stages of economic development, levels of AI proficiency, and industrial sectors. Table no. 6 presents the results of estimations that account for country-specific characteristics in the AI employment relationship.

Panel A of Table no. 6 discloses pronounced differences in the experience of AI's impact between developed and developing countries. High-income economies defined by World Bank are recognized as developed countries, otherwise as developing countries. The developed countries in the dataset are Australia, Austria, Belgium, Canada, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Qatar, Saudi Arabia, Singapore, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom and United States. The developing countries in the dataset are Argentina, Bangladesh, Brazil, Chile, China, India, Iran, Lebanon, Malaysia, Pakistan, Philippines, Poland, South Korea, Thailand and Turkey. In developed economies, advancements in AI are associated with a detrimental effect on employment rates. Specifically, a one-unit increase in AI proficiency corresponds to a 0.012% decrease in the employment rate, a finding that is statistically significant at the 1% level. The influence on labor income, however, is not pronounced. This suggests that in developed countries, while AI may displace certain jobs, the overall income levels of the workforce are maintained with relative stability. In stark contrast, developing nations confront more acute challenges. The enhancement of AI proficiency has exerted a significant and negative influence on both the employment rate and the labor income share in these countries, with respective coefficients of -0.074 and -0.087, both statistically significant at the 1% level.

A plausible economic interpretation is that developed countries, with their stronger technological and R&D capacities (Autor, 2019), are better equipped to integrate AI into their industrial sectors, thus cushioning the adverse impacts on employment and labor income. In contrast, developing countries, which often depend heavily on traditional industries, are inherently more vulnerable to the automation and disruption brought about by AI technologies (Arntz *et al.*, 2016). Moreover, these nations may grapple with labor market inflexibilities that hinder workers' ability to adapt quickly to emerging technologies, leading to diminished employment rates and exacerbated income inequalities between labor and other economic agents (Horne *et al.*, 2016).

Table no. 6 Panel B delves into the varied effects of AI on employment, considering the differing degrees of AI adoption across nations. Sort the countries according to their average AI Index from 2000 to 2022. The top 15 countries are classified as having a high AI level (threshold: average AI Index > 3.1), the middle 15 countries as having a medium AI level (threshold: average AI Index > 0.47), and the last 15 countries as having a low AI level. The advancement in AI level exerts a significant negative effect on employment rates in both high and low AI-level countries, with a particularly pronounced impact in the latter (coefficient: -0.074). This indicates that more sophisticated AI technology may lead to a contraction in job opportunities, and countries with less technological readiness are more susceptible to the disruptions caused by AI, potentially facing more severe unemployment issues. In contrast, countries with moderate levels of AI integration do not show a substantial effect of AI progress on employment rates. This could be because these nations are still in the nascent phase of AI technology assimilation, maintaining a more stable labor market status quo.

As for the labor income share, in high AI-level countries, the uptick in AI level correlates with a decline in the proportion of labor income. This might stem from the diminished bargaining power of workers in highly automated and intelligent settings, contributing to a widening income gap between labor and other economic agents. Conversely, in countries with an intermediate level of AI, the enhancement of AI has resulted in an increase in the labor income share, suggesting that moderate AI technology can bolster work efficiency and, in turn, elevate workers' earnings. Notably, in countries with low AI levels, AI development exerts no significant effect on the labor income share. This is likely due to these nations' weaker economic structures and technological progress, which limit the influence of AI on the distribution of labor income.

Table no. 6 Panel C analyzes the differential impacts of AI on employment across various sectors. Within primary industry, the integration of AI technology has bolstered the employment rate. This upward trend in employment can be credited to the heightened production efficiency that AI brings to agriculture and natural resource management, thereby spawning new job opportunities. Additionally, given that the primary industry is largely agrarian and labor-intensive by nature, it is inherently less prone to the detrimental effects of AI adoption. In contrast, the tertiary industry has witnessed a downturn in employment figures. Consisting mainly of service-based enterprises, this sector is highly susceptible to job displacement through advancements in AI, leading to a contraction in employment options.

As for secondary industry, there has been no notable change in employment levels. This stability may stem from the sector's diverse composition, where certain segments swiftly embrace automation while others continue to depend heavily on manual labor, maintaining a relatively steady employment trajectory.

Table no. 6 – National heterogeneity

Panel A: Economic level

Variable	*employ*		*labor_share*	
	Developed (1)	Developing (2)	Developed (3)	Developing (4)
AI	-0.012*** (-3.174)	-0.074** (-2.103)	-0.006 (-1.636)	-0.087*** (-2.793)
Control variable	Yes	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	601	194	476	160

Panel B:AI level

Variable	*employ*			*labor_share*		
	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)
AI	-0.020*** (-4.964)	-0.414 (-1.433)	-3.211* (-1.864)	-0.012*** (-3.202)	0.494** (1.972)	1.002 (0.840)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	328	316	151	254	251	131

Panel C: Different sector

Variable	*employ*		
	Primary (1)	Secondary (2)	Tertiary (3)
AI	0.008*** (5.527)	0.003 (1.537)	-0.011*** (-5.664)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes
N	795	795	795

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). The coefficients for the AI variable in Panel A related to developed and developing countries are obtained from regression models that account for country-specific characteristics. The coefficients in Panel B are calculated from regression models considering the different degrees of AI adoption. The coefficients for the AI variable in the employment rate in Panel C for primary, secondary, and tertiary industries are obtained from regression models specific to each industry. The control variables are control variables mentioned in Section 3.1.

5. DISCUSSION

The findings of this study align with an expanding body of research documenting the negative influence of AI on employment rates and labor income shares. The results support the theoretical framework of Acemoglu and Restrepo (2020c), in which AI-driven automation reduces labor demand through substitution effects. Similarly, the global evidence presented by Georgieff and Hyee (2022) and Hui *et al.* (2024) on employment-displacing effects of AI is consistent with the baseline results of this study. Building on these existing findings, this study offers unique contributions. By analyzing 22 years of global data from 2000-2022, it uncovers the differential impacts of AI across educational attainment, economic development levels, and industries. This long-term and comprehensive analysis not only provides a more in-depth understanding of AI's effects but also controls pandemic-related disruptions and validates results using alternative AI proxies.

The heterogeneity analysis in this study further enriches the understanding of AI's impact. For instance, while Frey and Osborne (2017) predicted higher automation risks for low-skilled workers, the results here show significant negative effects on groups with secondary and advanced education. This deviation from previous expectations indicates that AI's influence transcends traditional skill categorizations. This finding is in line with the discovery of Felten *et al.* (2023) that AI increasingly substitutes cognitive tasks previously done by high-skilled workers. The positive effect on the employment rates of those with basic education, as noted in Acemoglu and Restrepo (2020c), might be due to the challenges in automating manual tasks. These findings related to skill levels are closely tied to the overall impact of AI on employment, which in turn is a key factor influencing labor income shares.

Regarding labor income shares, the results of this study support the hypothesis of capital-biased technological change in Karabarbounis and Neiman (2014). However, this study goes a step further by directly linking this trend to AI adoption. The observed decline in labor shares contradicts the projection of stable income distribution until 2030 in Dolls *et al.* (2019). This contradiction, in the context of the employment-related findings, reflects how AI-induced changes in the labor market, such as job displacement and skill-based employment shifts, contributes to the acceleration of AI's economic transformation.

The differential impacts of AI on employment and income distribution also vary across countries. The discovery that developing countries experience more severe employment declines and income contractions provides empirical support for the theoretical arguments in Cheng and Peng (2018). These countries, lacking the adaptive capabilities of developed economies, are more vulnerable to AI-induced structural changes. This aligns with the warnings about automation risks in lower-income countries with rigid labor markets in Schlogl and Sumner (2020). The differential country-level impacts are intertwined with the sectoral impacts of AI.

The differential sectoral impacts identified in this study, with negative effects in the tertiary sector and positive effects in the primary sector, offer a new perspective. While previous studies often focused on the manufacturing sector (Graetz and Michaels, 2018; Wang and Dong, 2020), this study shows that service sectors are more vulnerable to disruption. This is consistent with the predictions about non-routine cognitive tasks in Brynjolfsson and McAfee (2011). The resilience of the primary sector emphasizes the role of labor-intensive industries in buffering automation effects. These sector-specific impacts are part of the broader picture of AI's influence on employment and income distribution, which is shaped by factors like skill levels and country-level economic characteristics.

6. CONCLUSIONS AND SUGGESTIONS

This longitudinal analysis of 22 years of global data (2000–2022) contributes to understanding AI's economic impacts by documenting significant negative effects on employment rates and labor income shares. In conclusion, our analysis yields two principal insights. Firstly, there is a discernible negative correlation between the adoption of AI and employment rates, as well as labor's proportion of income, in support of H1 and H3. Secondly, the influence of AI on employment and income distribution is marked by substantial heterogeneity among various groups and across nations, in support of H2. The impact is not uniform, with workers in different sectors and professions experiencing a spectrum of effects. Furthermore, the distinct economic frameworks and policy environments of individual countries give rise to a mosaic of outcomes related to AI integration.

Based on this, we propose the three recommendations below for how countries could address the challenge of AI employment.

First, making training and education investments. Improve education systems to foster lifelong learning and give opportunities for workers to learn new skills and information. Governments can help people adjust to the demands of evolving technology and occupations by funding online education and job retraining programs.

Secondly, encouraging new industries and innovation. Create new jobs by promoting innovation and growing sectors through policies. Encouragement of innovation and entrepreneurship, particularly in the sectors of AI, green technology, digitalization, and high technology, can assist in creating job possibilities and support economic growth.

Finally, promoting industrial reform and upgrading. Encourage traditional industries to adopt innovative technology to increase production efficiency, while also encouraging industrial upgrading and transformation. To ensure economic diversification and employment market stability, the government can provide financial and policy support.

However, several limitations merit consideration. First, while the Global AI Index captures interdisciplinary research capabilities, it may overstate real-world AI adoption in specific industries. Second, the macro-level analysis presented here does not disaggregate effects by occupation, leaving generative AI's impact on cognitive tasks underexplored. Third, although instrumental variables address endogeneity concerns, unobserved factors like national innovation policies could influence results.

Future research should address these gaps by incorporating micro-level data on AI adoption, exploring occupation-specific effects, and examining policy moderators. Longitudinal updates post-2022 are also critical to capture generative AI's accelerating impacts. By addressing these limitations, scholars can provide policymakers with more nuanced insights to navigate AI's transformative potential.

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ANNEX

Data detail

Data	Detail	Source	Frequency
Country	Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Canada, Chile, China, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, India, Iran, Israel, Italy, Japan, Lebanon, Luxembourg, Malaysia, Malta, Netherlands, New Zealand, Norway, Pakistan, Philippines, Poland, Portugal, Qatar, Saudi Arabia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, United Arab Emirates, United Kingdom, United States	/	Annual
employ	Employment rate of the population over 15 years old	International Labor Organization database	Annual
labor_share	Labor income as a percentage of GDP	World Bank database	Annual
AI	Global AI Index	AI Rankings	Annual
ln gdp	Logarithm of GDP per capita	World Bank database	Annual
ln population	Logarithm of the total population	World Bank database	Annual
ln school	Logarithm of average years of education	Global Data Lab database	Annual
aging	Proportion of the population aged 65 and older	World Bank database	Annual
indu	Proportion of value added by the secondary industry in GDP	World Bank database	Annual
urban	Proportion of the urban population in the total population	World Bank database	Annual
cpi	Consumer Price Index with 2010 as the base year	Global Data Lab database	Annual
open	Share of the value of imports and exports of goods and services in GDP	World Bank database	Annual
Robots stock	Stock of robots in use	International Federation of Robotics	Annual

Notes

[1]Narrow AI refers to systems designed for specific tasks, such as language translation and image recognition, commonly found in voice assistants and recommendation systems. In contrast, General AI refers to hypothetical systems that can understand, learn, and apply intelligence across a broad range of tasks, similar to human abilities (Poole and Mackworth, 2010).

[2] Considering that General AI remains a theoretical concept and has not yet been realized, the AI discussed in this article refers to Narrow AI.

[3]The original data is available at https://airankings.org/