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Artificial Intelligence and Unemployment: Moderating Effect of the Agglomeration Economy in Countries with Different Income Levels

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Abstract

This study analyzes the effect of adopting artificial intelligence (AI) on unemployment across countries with different income levels, while accounting for two key moderating factors: internet access and population density. To this end, panel data models were estimated for 61 countries over 2021–2024. The Global AI Index was used as a measure of technological development, and the unemployment rate was the dependent variable. In addition, control variables related to economic development, institutions, and education were included. The results indicate that, in high-income countries, AI use has a negative, statistically significant effect on unemployment. In contrast, in middle- and low-income countries, the impact of AI is less clear and not significant. This effect is reinforced when AI use is accompanied by better technological infrastructure, as measured by internet access. However, population density does not have a significant moderate effect on the relationship between AI and unemployment, especially in less developed economies.

Keywords: artificial intelligence; unemployment; internet access; population density; agglomeration economy.

JEL Classification: C23; J21; J64; O14

Inteligencia artificial y desempleo: efecto moderador de la economía de aglomeración en países con diferentes niveles de renta

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Resumen

El presente estudio analiza el efecto de la adopción de la inteligencia artificial (IA) sobre el desempleo en países con distintos niveles de renta, teniendo en cuenta dos factores moderadores clave: el acceso a internet y la densidad poblacional. Para ello, se estimaron modelos de datos de panel para 61 países durante el período 2021-2024. Se utilizó el Índice Global de IA como medida del desarrollo tecnológico, mientras que la tasa de desempleo se utilizó como variable dependiente. Además, se incluyeron variables de control relacionadas con el desarrollo económico, las instituciones y la educación. Los resultados indican que, en los países de ingreso alto, el uso de la IA tiene un efecto negativo y estadísticamente significativo sobre el desempleo. En contraste, en países de ingreso medio y bajo, el impacto de la IA es menos claro y no resulta significativo. Este efecto se ve reforzado cuando el uso de la IA se acompaña de una mejor infraestructura tecnológica, la cual se mide por el acceso a internet. Sin embargo, la densidad poblacional no ejerce un efecto moderador significativo en la relación entre la IA y el desempleo, especialmente en economías menos desarrolladas.

Palabras clave: inteligencia artificial; desempleo; acceso a internet; densidad poblacional; economía de aglomeración.

INTRODUCTION

The progressive adoption of artificial intelligence (AI) technologies has generated a profound transformation in global labor markets since the middle of the last decade, which has a differentiated impact on the volume, nature, quality, and distribution of employment, being particularly sensitive to the socioeconomic context and institutional capacities of the countries involved (Gmyrek et al., 2023). In this sense, AI has an impact not only on the number of jobs but, in a much more complex way, on the tasks that comprise them, the profiles that support them, and the adequate quality of the skills available.

However, the transformation of the global labor market started much earlier, in the 1990s, driven by digitalization, automation, and the reorganization of work. In the first case, it is conceived as a broad process that involves the incorporation of information and communication technologies (ICTs) and does not constitute a simple technical incorporation, but redefines models of labor organization (Bukhalo, 2024).

For Pedchenko et al. (2021), this digitalization is conceived as a driver of employment transformation, with its effects varying substantially across societies according to their levels of economic and technological development. The structural approach assumed by Pedchenko et al. (2021) is complemented by the position of Shkurat et al. (2024), who link the digitization process to the transformation of the economic system. From this perspective, recent technologies have changed not only employment but also the social relations of production, the design of jobs, and forms of economic interaction.

In the second case, task automation causes a displacement effect, rooted in classical economic theory on technological change and its relationship to labor productivity. However, since the 2000s, the theoretical focus has shifted from the replacement of entire workers to the replacement of specific tasks within an occupation (Drahokoupil & Jepsen, 2017; Georgieff & Hyee, 2022; Gmyrek et al., 2023; Kumar et al., 2024; Maria et al., 2025; Pignatelli et al., 2023).

Kindberg-Hanlon (2021) confirms that the effects of automation tend to be negative on total employment in the short run, being more pronounced in advanced economies; on considerations of the classical distinction between substitution effect and income effect, they concluded that the former dominates in most countries in the short run, although the latter manifests itself in a more delayed way, and only in those economies with high sectoral reconversion capacity. Specifically, the substitution effect refers to the ability of AI to replace human tasks, especially those that are routine and repetitive (Brynjolfsson & McAfee, 2011; Huang et al., 2019), while the income effect suggests that AI can increase productivity, potentially leading to new job creation and economic growth.

For AI to have a positive impact on employment, it is essential that it acts as a complement to human labor, rather than a substitute for it; this implies that the elasticity of substitution between AI and labor should be low, allowing both factors to enhance each other. Models such as Acemoglu and Restrepo's (2018) highlight that AI can increase productivity without displacing employment if it focuses on tasks that complement human skills.

So to obtain these positive effects Acemoglu and Restrepo (2018) assume that: a) the function has constant returns to scale; b) markets are competitive so that prices adjust efficiently and resources are optimally allocated across uses; c) factors of production (labor and capital) are substitutable in production; d) there are different levels of productivity for each task, and these productivities may vary depending on whether the task is performed by capital (automatically) or by human labor; e) the introduction of AI can enable both the automation of tasks and the creation of complementarities that increase the productivity of workers in non-automated tasks; and f) automation reduces the capital costs associated with marginal tasks, which means that AI technologies should facilitate production more economically.

This idea is complemented by Skill-Biased Technological Change (SBTC), which posits why AI tends to benefit high-skilled workers while displacing lower-skilled ones. From this perspective, technological progress does not affect the labor market neutrally, but rather increases the productivity of certain workers, reconfiguring the income distribution and causing labor polarization (Kanagarla, 2024; Kumar et al., 2024; Liang, 2024).

These findings could indicate that the effect is neither linear nor homogeneous, so that it is possible to identify studies that show positive, adverse, or neutral effects on the labor market. The first group includes research such as that of Guliyev et al. (2023), who establish that AI has a "displacement effect," but in the long term contributes to reducing unemployment by improving economic efficiency and creating new jobs, or that of Makridakis et al. (2020), who suggest that AI contributes to job creation in high-tech sectors, such as digital security, data analytics, and AI engineering and that although it replaces some jobs, it also provides new job opportunities for skilled workers.

In the second group, which proposes adverse effects, are the research of Brambilla et al. (2023) on the effects of automation in Chile, showing that young workers are more vulnerable to unemployment; that of Cea et al. (2024) who argue that automation could generate a significant increase in unemployment, especially if measures are not taken to mitigate its negative effects; and that of Sultana et al. (2024) who argue that AI and automation are transforming labor markets, displacing manual workers and increasing economic inequality. These results are corroborated by the work of Bordot (2022), Deswal and Sandhu (2024) and Liu (2023) who show that, in general, there is a positive and statistically significant association between higher AI adoption (whether measured by patents or exposure rates) and higher national unemployment, although the magnitude and robustness of this effect varies according to the method and population group analyzed.

In the third group, Mutascu (2021) and Mutascu and Hegerty (2023) establish that AI has a non-linear impact on unemployment, such that in situations of low inflation the adoption of AI reduces unemployment, but in other contexts the impact of AI on employment is neutral; while Qin et al. (2024) confirm that, in the short run, AI tends to increase unemployment, but in the long run, it contributes to the reduction of unemployment by improving productivity and creating new jobs.

When the comparison by income level of countries is incorporated in this analysis, the empirical evidence indicates that the impact of these transformations has not been homogeneous; in developed economies, the advance of automated technologies has stimulated the reduction of routine and low-skilled jobs, causing labor polarization phenomena, where high-skilled and low-income jobs increase simultaneously (Goos, 2018; Kindberg-Hanlon, 2021). Generally speaking, high-income countries are the most exposed to AI technologies in occupational terms (due to their service- and technology-based economic structures), but they also achieve higher complementarity rates, thereby reducing the negative net impact through active training policies and strong digital infrastructure (Pizzinelli et al., 2023). In turn, many of these countries have social protection systems that cushion the immediate effects of unemployment and facilitate the transition.

In contrast, in emerging and developing economies, the process of technological adoption has been slower but equally disruptive, affecting the future viability of labor-intensive sectors with high automation risk (Egana-delSol, 2019; Pedchenko et al., 2021). These low-income countries present significant structural challenges, such as high informality, low average schooling, dependence on the primary sector, and low investment in digitization, which reduces their exposure but also their capacity to generate new technological jobs (Du, 2024; Masood, 2024). These countries face a double threat: technological lag (by reducing their competitiveness) and low capacity to absorb displaced labor.

In middle-income countries, the displacement of unskilled workers is a recurrent phenomenon, as in Brazil and Mexico, where AI has driven a dual dynamic: on the one hand, job creation in technological sectors and, on the other, job destruction in traditional sectors. The study by González-Herrera et al. (2023) on the impact of AI in Mexico shows that employment in sectors such as manufacturing has decreased, while employment in the digital sector has increased, but only for those with specialized skills.

In China, AI has had a more diverse impact, characterized by the use of advanced technologies in urban areas, such as Beijing and Shanghai, which has driven growth in sectors such as advanced manufacturing and artificial intelligence applied to medicine. However, in rural areas, access to these technologies is more limited, resulting in stark labor inequalities between urban and rural areas. Qin et al. (2024) argue that automation has increased productivity, but only in sectors that have successfully adopted AI. In contrast, sectors that have not been able to integrate advanced technologies, such as traditional agriculture, have experienced significant job losses due to limited access to them.

The impact of AI in low-income countries has been more challenging, mainly due to technological barriers and a lack of infrastructure, as proposed by Munyaneza (2024), who indicates that while automation has generated employment opportunities in sectors such as education and health, access to these technologies remains limited, especially in rural areas. The lack of adequate digital infrastructure and the internet access gap in less urbanized areas limit the ability of workers to benefit from AI.

Thus, these findings not only show the differences in income levels between countries but also that the agglomeration economy can moderate the effects and speed of adjustment in the long run. Agglomeration economy refers to the concentration of economic activities in specific geographic areas, which generates benefits such as reduced costs, increased productivity, and easier access to labor markets and resources. In this context, internet access and population density could play a crucial role in moderating AI's impact on unemployment, as they facilitate the creation of more dynamic and resilient urban ecosystems in the face of technological change.

While there is empirical evidence of the moderating effect of digital infrastructure, it is very scarce regarding population density. In the first case, studies such as those by Gmyrek et al. (2023), Kanagarla (2024), Maria et al. (2025), and Pizzinelli et al. (2023) implicitly recognize that digital infrastructure and capabilities affect the adaptability of the workforce and its adaptation to technological change.

In this sense, the presence of good connectivity magnifies both the potential for displacement and the capacity for labor absorption in tasks that can be augmented, but not replaced, by AI, supported by an adequate institutional environment and the development of competencies that facilitate the insertion of the labor force into these activities.

With respect to population density, although it is recognized that countries with better infrastructure and digital access—which tend to coincide with dense urban areas—have greater exposure to the effects of AI, the effect of living in high-density areas versus low-density regions in terms of population is not specifically disaggregated, and there is no empirical evidence that recognizes this possible moderating effect.

Thus, several theoretical frameworks and precedents suggest that population density may play a moderating role in the relationship between AI adoption and unemployment. This potential effect is based on several structural and dynamic reasons specific to national labor markets; first, countries with high population density tend to benefit from agglomeration economies, characterized by the concentration of firms, institutions, infrastructure, and innovation networks. This urban aggregation fosters dynamism and facilitates knowledge sharing, generating greater labor opportunities and allowing the market to more easily absorb workers displaced by AI-driven automation processes (Bordot, 2022; Georgieff & Hyee, 2022; Webb, 2019).

In these contexts, the diversity of the business fabric and the flexibility of the labor market increase the possibilities for retraining and occupational mobility, which, according to Bordot (2022) and Webb (2019), facilitates the reallocation of affected workers to new industries or complementary jobs, which could cushion the negative impact of AI on unemployment rates. In addition, densely populated regions tend to have a comparatively more skilled workforce and superior access to training and continuing education programs, elements that promote adaptation to emerging technological requirements (Georgieff & Hyee, 2022).

In contrast, in countries or regions with low population density, the labor market tends to be more segmented and less dynamic. This limited economic diversification and sectoral specialization often hinder the reintegration of workers displaced by automation. However, such hypotheses have not been evaluated by quantitative analyses with multinational panel data and interaction models that allow us to identify the moderating effect of density.

In this regard, this paper examines the effect of AI on unemployment across countries with different income levels, while accounting for two key moderators of agglomeration economics: internet access and population density. Internet access is a key factor in integrating recent technologies, and in countries with limited connectivity, the benefits of AI may be limited, exacerbating employment inequalities. On the other hand, population density could influence how AI technologies are distributed and affect workers, especially between urban and rural areas.

The study, therefore, allows us to address key elements in the study of the effect of AI on the labor market, little explored in the literature; in the first case, the effect of AI on unemployment comparing between countries with different income levels and, secondly, how the moderating effect of the agglomeration economy enhances or limits the role of AI in the labor market. Special attention should be paid to population density, which, although theoretically it could enhance the effect of AI, empirical evidence on its moderating role has not yet been identified.

The starting point is therefore the hypothesis that the effect of AI on unemployment is not uniform across countries, but is mediated by income level and conditioned by factors associated with the agglomeration economy, specifically internet access and population density. It is expected that, in high-income economies, AI will have a negative impact on unemployment, given their greater institutional capacity, technological infrastructure, and skilled human capital. In contrast, in middle- and low-income countries, a zero or even positive effect on unemployment is anticipated, due to structural limitations that prevent them from taking advantage of the productive and labor benefits of AI. Furthermore, it is proposed that internet access reinforces AI's effect on employment, while population density, although theoretically facilitating technological diffusion and job creation, will not necessarily have a significant moderating effect in less developed contexts.

From the perspective of the literature gap, although there is a growing body of research on the effects of AI on the labor market, few studies empirically analyze how these effects vary across countries' income levels. Likewise, the literature has paid limited attention to the moderating role of variables associated with the agglomeration economy, such as population density, in the relationship between AI and unemployment. Most studies focus on advanced economies or sectoral analyses, leaving a significant gap in our understanding of how AI interacts with structural and territorial factors in developing economies. This study seeks to contribute to filling that gap by providing comparative empirical evidence on the differential impact of AI on employment, considering the moderating role of internet access and population density in countries with different income levels.

METHODOLOGY

To examine the effect of AI on unemployment using moderating variables such as internet access and population density, a sample of 61 countries grouped by income level (World Bank classification) was used: high income (42), middle income (9) and low income (10), for the years 2021, 2023 and 2024, depending on the availability of AI data.

For this purpose, the Global AI Index estimated by Tortoise Media (2024) was considered on the basis of three pillars, implementation (30 % of weight) covering talent (use of AI by public and private employees), infrastructure (solutions to expand digital infrastructure), and operating environment (legal, economic and cultural factors for the use of AI); innovation (40 % of the weight), which considers research (new ideas) and development (to generate knowledge and expand it); and investment (30 % of the weight) through the commercial ecosystem (goods and services needed for implementation) and government strategy (public decisions to deepen the use of AI).

Although the index was initially estimated for a smaller number of countries, it is now calculated for 83 countries, drawing on secondary databases on the behavior of developers, scientists, professionals, government, educational institutions, companies, investors, legislators, and employees, among others. This measurement, comprising 122 indicators, uses a scale from 0 to 100, where values close to 0 indicate little development and values close to 100 indicate extensive development of the pillars.

The dependent variable was the unemployment rate, estimated as the proportion of the economically active population aged 15 and over who are unemployed, obtained from the International Labor Organization (ILO, 2024) database.

As control variables we included constant gross domestic product per capita (World Bank, 2024), some institutional dimensions of the index of economic freedoms (Heritage Foundation, 2024) that can encourage the reduction of unemployment such as property rights (rule of law); business freedom and labor freedom (regulatory efficiency); trade freedom and investment freedom (open markets). These dimensions are evaluated on a scale of 0 to 100, where 100 indicates greater economic freedom. Additionally, education was used as a proxy variable to estimate Sustainable Development Goal (SDG) 4, based on the Sustainable Development Report (SDR; Sachs et al., 2024).

Finally, as moderating variables of the agglomeration economy, we considered internet access (percentage of the population with internet access) obtained from Our World in Data based on the work of Ritchie et al. (2023), and population density (World Bank, 2024), using estimates from the population projections of each country for the study period.

The aim is then to contrast the existence of an inverse effect of AI (AI_{it}) on unemployment (UN_{it}) at the global level and by countries with different income levels, which is reinforced by the presence of higher connectivity ($Inter_{it}$) and population density ($dens_{it}$). We considered GDP per capita ($GDPper_{it}$) and economic freedom indicators (EF_{it}) as control variables using panel data for the three years and the 61 countries in the sample, according to the specification in Equation 1.

$$UN_{it} = \alpha + \beta_1 AI_{it} + \beta_2 GDPper_{it} + \beta_3 EF_{it} + \beta_4 Edu_{it} + \beta_5 Inter_{it} + \beta_6 dens_{it} + \varepsilon_{it} \qquad (1)$$

Initially, a model like the one proposed in Equation 1 was estimated without the moderating effect of the agglomeration economy variables, to later incorporate, in each case (global and by income level), the interaction of each one, as shown in Equations 2 and 3.

$$UN_{it} = \alpha + \beta_1 AI_{it} + \beta_2 GDPper_{it} + \beta_3 EF_{it} + \beta_4 Edu_{it} + \beta_5 Inter_{it} + \beta_6 dens_{it} + \beta_7 AI_{it} * dens_{it} + \varepsilon_{it} \qquad (2)$$

$$UN_{it} = \alpha + \beta_1 AI_{it} + \beta_2 GDPper_{it} + \beta_3 EF_{it} + \beta_4 Edu_{it} + \beta_5 Inter_{it} + \beta_6 dens_{it} + \beta_7 AI_{it} * Inter_{it} + \varepsilon_{it} \qquad (3)$$

Given the limited time horizon, a static panel data estimation was proposed to explain the existing heterogeneity in the data, either as differences between individuals or as the effect of chance. This unobservable heterogeneity, as part of the estimation error, introduces covariance between it and the explanatory variables, preventing the model assumptions from being met and leading to bias in the estimation (Montero, 2011).

To solve the estimation difficulties, the fixed-effects model recognizes the existence of this non-zero covariance and performs the estimation using the difference of each variable in relation to its average if the unobservable heterogeneity lies in the individual differences. While the random-effects estimation, by assuming that heterogeneity is a product of chance, assumes that the covariance is zero.

The selection between the fixed-effects and random-effects models was made using the Hausman test, whose null hypothesis is that the random-effects model is the correct one. In case of rejection of the null hypothesis, it is necessary to validate the fixed effects model in terms of the absence of autocorrelation (Wooldridge test) and heteroscedasticity (modified Wald test). In this estimation, the limited time observations make it impossible to evaluate for autocorrelation, but in the presence of heteroscedasticity, it will be necessary to adjust the estimation using the panel-corrected standard error (PCSE) method.

RESULTS

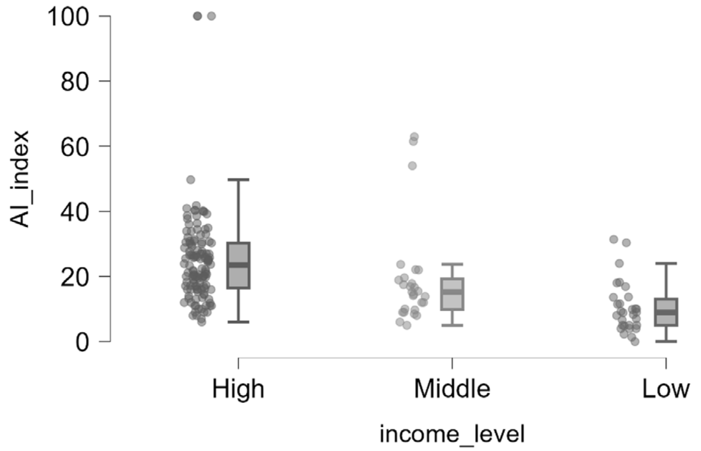
The AI index averaged 21.84 points during the study period, with higher scores for high-income countries (25.16), followed by middle-income countries (19.11) and low-income countries (10.39), as shown in Figure 1. Despite differences in income levels, high- and middle-income countries exhibit greater dispersion, while low-income countries show more homogeneous behavior.

The United States, China, England, and Canada stand out in the best positions, while the countries with the lowest performance within the sample are Kenya, Nigeria, and South Africa, so it seems that it is in the high-income countries where the best results are obtained in the components of the AI index.

As shown in Figure 2, when detailing the performance in each of the pillars analyzed, high-income countries achieve higher values, followed by middle-income countries and low-income countries, all characterized by an operating environment with the best performance, government strategies, and infrastructure that support a favorable environment for promoting the use of AI.

Figure 1.

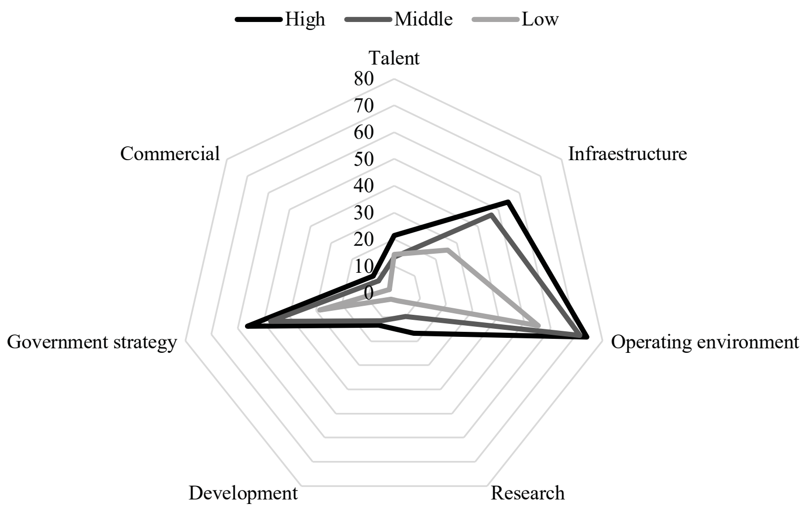
Average AI Index by Country Groups by Income Level (2021–2014)



Source: Based on Tortoise Media (2024) data.

Figure 2.

Average AI Index by Dimension and Country Group by Income Level (2021–2024)



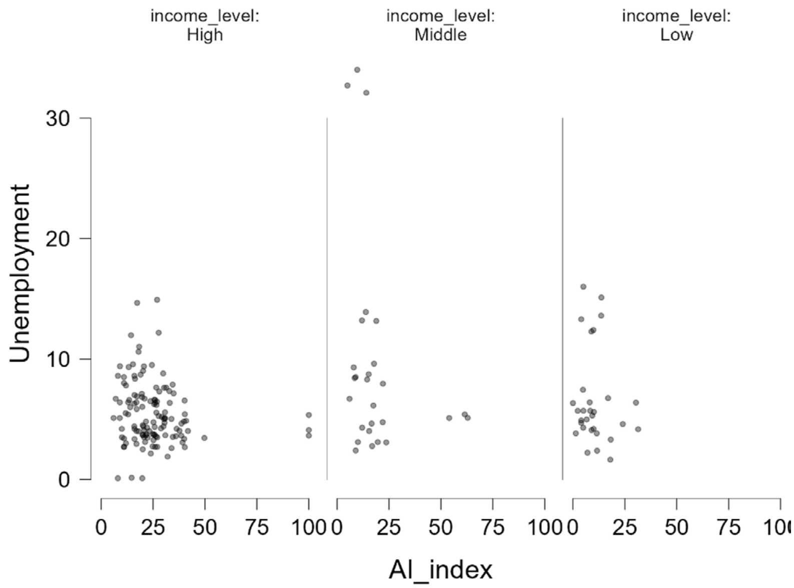
Source: Based on Tortoise Media (2024) data.

There are strong restrictions for talent, research and development, and commercialization, which do not seem to depend on the country's income but on the general conditions for innovation and the building of competencies that empower human talent for the use of IA, whose challenges are even greater in low-income countries.

If we analyze the relationship between IA performance and unemployment in the high-income group, most of the data are concentrated at low unemployment levels, regardless of the IA index value. This suggests that in higher-income regions, unemployment tends to be low even when the IA index varies. In the middle-income group, the points are more dispersed, with some higher unemployment values, especially when the AI index is low or medium. This could indicate that, in middle-income areas, unemployment does not follow a clear trend with AI use. In the low-income group, a clear dispersion of points is observed, although unemployment levels are generally higher, regardless of the AI index (Figure 3).

Figure 3.

Relationship between Unemployment and Average IA Index by Income Level (2021–2024)



Source: Based on Tortoise Media (2024) and ILO (2024) data.

Despite AI adoption, unemployment does not decrease notably in these areas, which may be due to a lack of infrastructure, education, or the capacity to implement advanced technologies effectively. However, high-income areas seem to be less affected by unemployment despite variations in AI adoption, whereas in low- and middle-income regions the relationship between AI and unemployment is less evident, suggesting additional structural challenges in these areas in leveraging AI to reduce unemployment.

To test this relationship, four models were estimated (global, high-income, middle-income, and low-income) without considering the moderation of the agglomeration economy variables. As shown in Table 1, for the model with the total number of countries, IA is statistically significant and with the expected sign (negative), which would indicate that, on average an increase in the IA index results in a reduction of the unemployment rate, which also occurs in middle and high income countries, although in these cases they are not significant. A direct relationship can be identified in low-income countries, where higher levels of IA use appear to raise unemployment, possibly due to penetration of the service sector and low-skilled jobs that generate labor polarization.

For the global model and high-income countries, random effects were selected based on the Hausman test; for low- and middle-income countries, fixed effects were selected, as the null hypothesis of the test was rejected. In both cases, it was not possible to validate the assumptions of no autocorrelation and homoscedasticity using the Wooldridge and modified Wald tests, respectively; therefore, the corrected standard errors for the panel model were estimated.

With respect to the variables related to the agglomeration economy, Internet access was significant and with a negative sign in all estimates, but it was only significant in middle and high-income countries, so it could be expected that improvements in terms of connectivity represent reductions in the unemployment rate, due to remote work modalities, increased productivity, and even improvements in educational levels. As for population density, the effects are ambiguous; in low- and middle-income countries, higher density is associated with higher unemployment, though this effect is significant only in middle-income countries. Although the concentration of people and companies in urban areas could promote job creation, structural limitations prevent this from happening effectively, such that the lack of adequate infrastructure, such as transportation and basic services, limits the development of these areas, making the supply of jobs unable to absorb population growth.

Table 1.

Unmoderated Agglomeration Economics Unemployment Estimates

	Global model (RE)	Low income (FE pcse)	Medium income (FE pcse)	High income (RE)
AI	-0.0373**	0.0089	-0.9458***	**-0.0136**
	(0.0183)	(0.0461)	(0.1415)	**(0.0163)**
GDP per capita	-0.00003**	0.0005	-0.0021***	-0.00001
	(0.00001)	(0.0003)	(0.0004)	(0.00001)
Property rights	-0.0135	0.2073***	0.1355	-0.0381**
	(0.0146)	(0.0324)	(0.0992)	(0.0193)
Business freedom	0.0188	-0.0902**	-0.4798***	0.0369*
	(0.0172)	(0.0400)	(0.1265)	(0.0200)
Labor freedom	0.0158	0.0680*	0.1040	0.0098
	(0.0145)	(0.0356)	(0.1456)	(0.0151)
Business freedom	0.0958***	-0.0798**	-0.5122***	0.0856**
	(0.0227)	(0.0393)	(0.1423)	(0.0402)
Investment freedom	0.0253	0.2739***	-0.4652***	0.0071
	(0.0227)	(0.0387)	(0.0643)	(0.0223)
Education	-0.0018	0.0500**	0.8845***	0.0025
	(0.0092)	(0.0252)	(0.1956)	(0.0090)
Internet access	-0.0285	-0.0063	-0.6156***	-0.0638*
	(0.0219)	(0.0271)	(0.1120)	(0.0331)
Population density	-0.0006	0.0056	0.1633***	-0.0004
	(0.0005)	(0.0043)	(0.0410)	(0.0003)
Constant	0.5058	-17.620***	91.868***	4.6554
	(3.3563)	(4.264)	(13.524)	(5.3158)
Wald/F test	26.21***	580.01***	219.32***	31.47***
R2 overall	0.0584			0.1113
R2 within	0.1734			0.2730
R2 between	0.0541			0.0943
Rho	0.9522			0.8868
Hausman test	5.18	21.97***	93.47***	8.25

Note. Values in parentheses are standard errors. Significant at 1 % (***), 5 % (**), and 10 % (*).

Source: Author's elaboration.

When the interaction with the moderate variable of Internet access is incorporated, it is expected to reinforce the effect of IA use on unemployment, so that greater connectivity reduces unemployment. Table 2 shows the results of the estimation, including the interaction, so that a significant effect with the expected sign can only be identified in middle- and high-income countries.

Table 2.

Unemployment Estimates with Moderation of Internet Access (Agglomeration Economy)

	Global model (RE)	Low income (FE pcse)	Medium income (FE pcse)	High income (RE)
AI	0.0706	0.08659	0.2141	0.3523
	(0.0869)	(0.0932)	(0.7780)	(0.2444)
AI* internet access	-0.0012	-0.0019	-0.0142*	-0.0039*
	(0.0009)	(0.0021)	(0.0071)	(0.0020)
GDP per capita	-0.00004***	0.0004	-0.0021***	-0.00001
	(0.0001)	(0.0003)	(0.0004)	(0.0002)
Property rights	-0.0104	0.1963***	0.1648*	-0.0380**
	(0.0148)	(0.0341)	(0.0948)	(0.0192)
Business freedom	0.0197	-0.0853**	-0.4827***	0.0413**
	(0.0171)	(0.0406)	(0.1140)	(0.0201)
Labor freedom	0.0168	0.0713**	0.0777	0.0121
	(0.0144)	(0.0347)	(0.1330)	(0.0151)
Business freedom	0.0938***	-0.0751*	-0.4119***	0.0773*
	(0.0295)	(0.0387)	(0.1437)	(0.0404)
Investment freedom	0.0291	0.2666**	-0.4526***	0.0088
	(0.0228)	(0.0386)	(0.0646)	(0.0223)
Education	-0.0042	0.0422	0.7894***	0.0018
	(0.0094)	(0.0272)	(0.1892)	(0.0090)
Internet access	-0.0065	0.0209	-0.3889*	0.0102
	(0.0279)	(0.0409)	(0.2114)	(0.0628)
Population density	-0.0006	0.0051	0.1347***	-0.0004
	(0.0005)	(0.0042)	(0.0424)	(0.0003)
Constant	-1.3062	-17.500***	74.986***	-2.0268
	(3.6405)	(4.121)	(19.552)	(6.9057)
Wald/F test	28.00***	557.54***	202.56***	34.11***
R2 overall	0.0674			0.1039
R2 within	0.1824			0.3027
R2 between	0.0631			0.0851
Rho	0.9528			0.8827
Hausman test	4.14	17.91*	41.18***	10.01

Note. Values in parentheses are standard errors. Significant at 1 % (***), 5 % (**), and 10 % (*).

Source: Author's elaboration.

In middle- and high-income countries, AI, together with Internet access, improves productivity and creates new job opportunities, significantly reducing unemployment. The technological infrastructure and human capital in these countries allow the benefits of AI to be effectively harnessed, boosting job creation and reducing unemployment.

In contrast, in low-income countries, the relationship is not significant, suggesting that AI and internet access do not have a positive impact on unemployment. This could be due to structural constraints, such as poor infrastructure, low levels of education and training, and a lack of public policies that facilitate adaptation to new technologies. In these contexts, AI does not create enough jobs or improve productivity significantly, which may even increase unemployment, so that the factors do not complement each other, but the substitution effect occurs.

With respect to the incorporation of the moderating effect of population density, Table 3 shows that, in no case is the effect significant; AI is significant and evidences an inverse relationship at middle- and high-income levels, as well as at the individual level (high income).

This may be due to several factors that affect how AI influences the labor market, especially in relation to population density, such as economic structures, lack of infrastructure and skills, lack of public policies and institutionality, inequality in the benefits of AI. In low- and middle-income countries, urban areas may have high population density, but informal economies and lack of adequate access to technologies limit the effective adoption of AI, which means the interaction between population density and AI does not have a significant impact on unemployment.

Technology infrastructure and the availability of skilled labor play a crucial role in how AI can reduce unemployment. In densely populated areas, especially in low- or middle-income countries, the infrastructure to implement AI-based solutions may be deficient. Moreover, the lack of training and education in technology makes it difficult for AI to generate employment opportunities, even in areas with high population density. Additionally, the absence of effective public policies to encourage the use of AI and job training may prevent population density and AI from having a significant impact on job creation; in these contexts, even if there is a high population density, the lack of policies that support technological adoption and digital skills training may render the relationship between AI and unemployment insignificant.

In low- and middle-income countries, AI may primarily benefit specific sectors of the economy, such as technology industries, but not necessarily higher employment sectors or the unskilled labor force. This may render the interaction between population density and AI insignificant, as AI's effects are not evenly distributed across the population.

Table 3.

Unemployment Estimates with Moderation of Population Density (Agglomeration Economy)

	Global model (RE)	Low income (FE pcse)	Medium income (FE pcse)	High income (FE pcse)
AI	-0.0424**	0.0831	-1.0610***	-0.0179*
	(0.0188)	(0.1114)	(0.2154)	(0.0103)
AI* density	0.00001	-0.0002	0.0014	0.00001
	(0.00001)	(0.0002)	(0.0021)	(0.00001)
GDP per capita	-0.00003**	0.0005	-0.0021***	-0.00002**
	(0.0001)	(0.0003)	(0.0004)	(0.00001)
Property rights	-0.0139	0.2150***	0.1564	-0.0494
	(0.0145)	(0.0332)	(0.1052)	(0.0331)
Business freedom	0.0185	-0.0905**	-0.4766***	0.0556
	(0.0171)	(0.0393)	(0.1216)	(0.0512)
Labor freedom	0.0165	0.0721**	0.0896	-0.0161
	(0.0144)	(0.0365)	(0.1432)	(0.0223)
Business freedom	0.0971***	-0.0883**	-0.4458**	-0.0641
	(0.0294)	(0.0399)	(0.1755)	(0.0506)
Investment freedom	0.0274	0.2784***	-0.4417***	0.0629***
	(0.0227)	(0.0384)	(0.0778)	(0.0241)
Education	-0.0011	0.0500**	0.8118***	0.0268
	(0.0092)	(0.0249)	(0.2179)	(0.0179)
Internet access	-0.0317	-0.0082	-0.5589***	-0.0109**
	(0.0220)	(0.0271)	(0.1339)	(0.0518)
Population density	-0.0010	0.0086	0.1122	-0.0008**
	(0.0006)	(0.0058)	(0.0859)	(0.0003)
Constant	0.5595	-18.520***	90.475***	15.568**
	(3.3611)		(14.186)	(6.2060)
Wald/F test	27.88***	522.09***	198.78***	48.37***
R2 overall	0.0594			
R2 within	0.1832			
R2 between	0.0548			
Rho	0.9538			
Hausman test	10.77	31.64***	49.81***	15.39*

Note. Values in parentheses are standard errors. Significant at 1 % (***), 5 % (**), and 10 % (*).

DISCUSSION

The literature proposes that AI could have differentiated effects on unemployment according to the socioeconomic context and institutional capacity of countries, particularly the effects of AI on the labor market would not be homogeneous but would vary according to the income level of countries and technological and institutional capabilities. This empirical analysis confirms and extends these assertions by revealing significant differences in AI's effects on unemployment across high-, middle-, and low-income countries, with moderating interactions such as Internet access and population density.

The results show that, in high-income countries, the use of AI has a significant negative effect on unemployment, meaning that, on average, an increase in the AI index is associated with a lower unemployment rate. This finding is consistent with Brynjolfsson and McAfee (2011), who argued that AI and emerging technologies can increase productivity without necessarily generating a loss of employment, especially in advanced economies with an elevated level of workforce skills.

This positive effect in high-income countries is also in line with Acemoglu and Restrepo's (2018) theory, which stresses that AI can be complementary to human labor when both factors are mutually enhancing, especially in high-tech and innovation sectors. This, in turn, creates new job opportunities by increasing productivity in sectors such as information technology, AI engineering, and cybersecurity.

Furthermore, the interaction between AI and internet access shows a positive impact in high-income countries. The results indicate that greater internet access boosts the impact of AI, which further reduces unemployment. This finding supports the theory of agglomeration economics and technology distribution mentioned in the introduction, which argues that internet access facilitates the integration of AI into labor markets and improves productivity. Digital infrastructure and favorable public policies in these countries enable effective adoption of AI, which contributes to the creation of skilled jobs.

In contrast, the results for low- and middle-income countries indicate a positive but non-significant relationship between IA and unemployment. In low-income countries, even when the AI index improves, unemployment does not decrease significantly. This is due to structural constraints such as a lack of technological infrastructure, low workforce skills, and low internet connectivity, which prevent AI from generating the expected benefits in the labor market.

This result is consistent with the findings of Gmyrek et al. (2023), who observed that, in developing economies, automation and AI can increase unemployment in low-skilled sectors. This occurs because the jobs AI replaces in these contexts tend to be unskilled, in sectors such as manufacturing or services, which account for a large share of the labor force in low-income countries.

In middle-income countries, although the relationship is also non-significant, the results show a greater dispersion, suggesting that the impact of AI on unemployment is more uncertain and depends on the country's economic, social, and political conditions. As middle-income countries are in a transition phase, with developing technological infrastructure and a workforce gradually adapting to AI, the effects on employment are harder to predict and more volatile.

As for population density, the results show that this moderate variable does not have a significant effect on any of the groups of countries according to their income level. Although it was expected that higher population density in urban areas could facilitate the adoption of AI through talent aggregation, access to markets, and better infrastructure, the lack of adequate conditions, such as supportive public policies and job training, limits its impact. In low- and middle-income countries, insufficient infrastructure and unequal access to technology are factors that prevent population density from facilitating AI-driven job creation.

This finding is also consistent with Bordot (2022) and Georgieff and Hyee (2022), who suggest that in economies with less developed labor structures and limited technological adoption policies, the benefits of economic agglomeration do not materialize as expected. Although urban areas may have higher population density, without adequate infrastructure and policies that promote education and technological training, unemployment does not decrease.

The results of this research are partly consistent with Kindberg-Hanlon's (2021) findings, which stated that the effects of automation on employment vary across countries' levels of economic development. High-income countries have more capacity to benefit from AI, thanks to their advanced infrastructures and highly skilled human capital. In contrast, in low- and middle-income countries, structural challenges limit the benefits of AI and the ability to integrate these technologies effectively into the economy.

The literature also suggests that the substitution effect of AI is more pronounced in economies with a large share of manual or low-skilled jobs, as reflected in low- and middle-income countries, where automation mainly replaces unskilled workers. This phenomenon has been extensively documented by Brynjolfsson and McAfee (2011) and Huang et al. (2019), who stated that the effects of AI tend to displace workers in routine tasks, which aggravates the employment situation in traditional sectors.

This study has provided valuable insights into the impact of AI on employment, but it also has several limitations that future research should address. First, the analysis focused on a relatively short time horizon, limiting understanding of the long-term effects of AI on the labor market.

Another key limitation is the exclusion of important contextual variables, such as the quality of the education system and specific public policies, which may significantly influence the relationship between AI and unemployment. Although some control variables were included, we did not delve into factors that could moderate AI’s effects, such as the level of urbanization or country-specific economic conditions. In this regard, future research could examine how these factors affect AI adoption and its effects on employment.

Also, the measurement of AI in this study was based on an aggregate index, which does not capture differences in the types of AI and how these may have an unequal impact on employment by sector. For example, process automation in industrial sectors could have a different impact than AI in services. A more detailed analysis of how diverse types of AI affect specific sectors could yield more accurate and relevant results.

Population density, as a moderator of the relationship between AI and employment, did not have a significant impact in this study, opening a research gap on how factors such as digital infrastructure or informal labor markets may influence AI's effects. In places with high population density, a lack of adequate technological infrastructure, and a lack of vocational training policies may limit the benefits of AI, requiring further analysis of the local conditions affecting this interaction.

Finally, the study focused mainly on the effects of AI on total employment but did not address in depth the inequalities that may arise from automation. AI may polarize the labor market, creating high-skill jobs in some sectors while leaving lower-skilled workers unemployed or in precarious jobs. Future research should analyze how AI contributes to income inequality and how it can be better redistributed to avoid negative effects on the most vulnerable groups.

The results should be interpreted with caution, given that the relationship between AI and unemployment may be affected by uncorrected endogeneity derived from both reverse causality and omitted variables. The scarcity of time-series observations, which limits the availability of robust identification techniques (such as instrumental variables or dynamic designs), hinders the ability to establish clear causal relationships.

In addition to the methodological limitations already noted, it is important to highlight that the estimated effects may vary significantly between regions even within the same income group, suggesting that unobserved local factors—such as productive structure, digital governance, labor informality, or innovation capacity—may be moderating the relationship between AI and unemployment. This regional heterogeneity reinforces the idea that there is no single, transferable policy for all countries. In this sense, public policy implications must be contextualized: while in high-income economies it may be effective to promote the adoption of AI through tax incentives and retraining programs, in middle- and low-income countries it is more urgent to strengthen digital infrastructure, expand access to quality education, and design labor protection strategies to accompany the technological transition. The absence of causal identification in this study implies that policy recommendations should be treated as suggestions based on associative patterns rather than guaranteed effects, and that local evaluations and pilot projects should precede large-scale implementation.

CONCLUSION

The results reveal that, while in advanced economies the impact of AI tends to be positive for employment, with Internet access exerting a significant moderating effect, in low- and middle-income countries the impact is more uncertain and often not significant.

First, in high-income countries, the results confirm the hypothesis that AI adoption negatively and significantly affects unemployment. This is mainly because these countries have adequate infrastructure, highly skilled human capital, and public policies that favor the adoption of recent technologies. On the other hand, in middle-income countries, although AI also has a negative effect on unemployment, this effect is not significant. The results suggest that, although AI improves productivity and contributes to the expansion of some sectors, structural constraints in these countries–such as the lack of adequate technological infrastructure and a less skilled labor force–prevent the benefits of AI from translating into a significant reduction in unemployment.

As for low-income countries, the results show that, although AI has the potential to improve productivity, its impact on unemployment is null or positive, but not significant. This could be explained by several structural and social factors: low internet connectivity, a lack of vocational training, and limited investment in technological innovation in these countries limit AI's ability to generate quality employment. Indeed, in these contexts, automation brought about by AI can have a substitution effect, displacing unskilled workers in sectors where automation is more feasible. However, as low-income economies tend to be more oriented towards labor informality and have fewer resources to take advantage of emerging technologies, the overall effect of AI on unemployment is less evident.

The analysis of population density has also shown interesting results, since, although it could be expected that higher population density favors the adoption of AI through the agglomeration economy, the results indicate that, in low- and middle-income countries, population density does not have a significant effect on the relationship between AI and unemployment. In contrast, in high-income countries, where structural conditions are more favorable, the agglomeration economy allows the benefits of AI to be distributed more efficiently, creating new jobs and reducing unemployment rates.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

AI USAGE STATEMENT

The authors declare that no AI was used in the conceptualization or writing of this article.

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