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# Artificial Intelligence and the Future of Work: Evidence and Policy Guidelines for Developing Economies

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# Artificial Intelligence and the Future of Work: Evidence and Policy Guidelines for Developing Economies

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# ABSTRACT

## Artificial Intelligence and the Future of Work: Evidence and Policy Guidelines for Developing Economies*

This article offers a comprehensive review of Artificial Intelligence's (AI) effects on global labour markets, with a particular focus on developing economies. Drawing on an extensive body of evidence, it demonstrates that AI's disruptive potential diverges markedly from earlier waves of automation, extending its reach into occupations once deemed insulated—especially those demanding advanced education and complex cognitive abilities. The analysis reveals significant heterogeneity in AI exposure across countries at different development stages and among workers distinguished by skill sets, educational attainment, age, and gender, underscoring its unequal distributional consequences. To harness AI's benefits while safeguarding vulnerable groups, we propose four strategic policy levers: bolstering digital infrastructure, expanding vocational training and lifelong upskilling programmes, formalising labour markets, and integrating AI tools within social protection delivery. Collectively, these measures foster a human centred adoption of AI, bridge the digital divide, and promote inclusive growth, thereby mitigating adverse impacts on employment and wages.

**JEL Classification:** J23, J24, J31, O1, O33

**Keywords:** artificial intelligence, labour market, inequality, automation, social protection

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## Table of Contents

I. Introduction 2

II. Literature review 7

III. Methods 16

IV. Results 19

A. Differences between countries 19

B. Exposed occupations to AI 22

C. Skills of individuals exposed to Artificial Intelligence 25

D. Education of individuals exposed to Artificial Intelligence 27

E. Age of individuals exposed to AI 29

F. Gender of individuals exposed to AI 30

G. Inequality 31

H. Others 32

V. Policy proposals 33

A. Workers' Concerns 34

B. Access to internet services 36

C. Social protection 37

D. Labour market formalisation 40

E. Vocational training 42

F. Worldwide actions and initiatives 44

VI. Conclusions 46

VII. Bibliography 50

## I. Introduction

The development of technology has led to rapid and transformative changes in our societies. Advancements in healthcare and environmental protection, as well as the emergence of new ways of working, have significantly impacted various aspects of daily life. The internet, as a key driver of the creation, diversification, and dissemination of information, has been an essential resource for the adoption of technology and, consequently, for the development of nations. For instance, individuals with access to high-speed internet experience a 13.2% increase in employment opportunities, while total employment per company rises by up to 22%, and exports per company nearly quadruple (World Bank 2024). These changes, although disruptive, have been gradually and unevenly integrated, depending on the material conditions and level of development of each country. This process generates varying effects and development gaps that can persist over time, both within countries and between them.

Artificial Intelligence (AI), together with the Fourth Industrial Revolution, poses significant challenges concerning the social changes it may induce, particularly in terms of the future of work regarding its organisation and productivity, among other dimensions. Much like access to the internet, the development, accessibility, and utilisation of Generative Artificial Intelligence present the possibility that many jobs may become simpler and quicker to perform, but also some parts of the labour market could be replaced by this technology. These possibilities, whose magnitude remains unknown, present challenges that need to be addressed through public policies that ensure sustainable adoption by facilitating adaptation to it, as well as mitigating adverse consequences. Therefore, understanding and identifying what these challenges are and what we currently know about them becomes paramount.

This research systematically reviews the existing literature on the impacts of Artificial Intelligence on labour market outcomes and the broader socio-economic landscape worldwide. It also identifies potential strategies to mitigate adverse effects, capitalise on opportunities for inclusive growth, and enhance human development through people-centred digital technologies. In doing so, the study proposes policy measures focusing on formalisation, social protection, and training to address the consequences of digital transformation, aiming to expand capabilities and promote human development, particularly among vulnerable groups. Accordingly, the research question addressed in this paper is: How does exposure to Artificial Intelligence influence labour market outcomes across both developed and developing economies, and what policy strategies can effectively mitigate adverse effects while promoting inclusive growth?

To examine the future of work and the challenges arising from the adoption and widespread use of Artificial Intelligence, we will use the recent automation process—about which we have more extensive evidence—as a starting point. By doing so, we aim to identify the potential differences between this new technology and recent automation efforts, recognising that the full scope and potential of AI remain unclear. However, emerging evidence suggests that the skill sets and occupations at risk diverge significantly from those mostly affected by automation, as detailed in this document.

For instance, in the case of automation, evidence indicates that it has impacted and deepened wage inequality in the United States (Acemoglu and Restrepo 2019), and has affected skills and abilities such as knowledge of fine arts and several psychomotor abilities, with subsequent consequences for the labour market in OECD countries (Lassébie and Quintini 2022). Moreover, findings for developing countries and Latin America suggest even more pronounced potential impacts (Egana-delSol and Joyce 2020;

Egana-delSol et al. 2022). Meanwhile, Autor (2019) argues that certain factors, such as high levels of skill specialisation and the attainment of advanced higher education, enable protective or adaptive measures that minimise the impact of automation on these segments of the labour market. This result aligns with evidence from Latin America (Egana-delSol et al. 2022; Egana-delSol, Cruz, and Micco 2022).

However, Artificial Intelligence may have an important impact in economies while amplifying inequalities by increasing capital income and with different effects for workers according to age and educational background (Acemoglu and Restrepo 2022). Different results will depend on both, complementarity of occupations and exposure to artificial intelligence and differ for advanced and emerging economies (Cazzaniga et al. 2024). Historically, part of this differentiated impact has been influenced by institutional arrangements and power relations that mediate the transmission of benefits from technological advancements (Acemoglu and Johnson 2024) and by the extent of relevant public policies.

In this article, we explore how Artificial Intelligence (AI) may affect the future of work. To this end, we first provide a brief overview of the current understanding of how this disruptive new technology could impact existing employment and the labour force. Although there is a significant degree of uncertainty due to the recent emergence of this technology and the rapid pace of its development, we will demonstrate that the various efforts to conceptualise, model, and evaluate its future impacts consistently indicate that these effects will differ according to the country's level of development, workers' skills, age range, gender, and the sectors in which they are employed.

Given that Artificial Intelligence (AI) and Generative AI have not yet been widely adopted and remain largely in a pilot stage across various industries, there is still limited empirical evidence of their impact on the labour market beyond specific cases (Brynjolfsson, Li, and Raymond 2024; Brynjolfsson and Unger 2023). The stage of implementation is even more nascent in developing economies, where analysis has often focused on estimating the areas and jobs that will be most affected when this technology becomes widespread (Gmyrek et al. 2024; Benitez and Parrado 2024). Indeed, to understand the potential effects of AI on developing economies and the associated public policies required for optimal deployment, we will first review the existing evidence related to automation processes. Following this, we will examine studies that estimate the risks of exposure to AI, particularly those based on task-based and automation models.

These models are particularly valuable as they allow for conceptualising AI as a technology capable of performing an additional set of tasks beyond those potentially addressed by automation. However, it is important to emphasise that the mere existence of a technology's capacity to perform certain tasks is not a sufficient condition for the replacement of labour by technology. Other factors influence this decision, including labour conditions, wages, the cost of capital, complementary human capital for the new technology, and other contextual considerations.

Consequently, the progress achievable through this technology will be determined by how public policies address the mitigation of these differential effects and guide its development towards prioritising societal sustainability. Therefore, we will also discuss possible policies that countries could adopt, both collectively and individually, to harness this innovation, always bearing in mind that these measures depend on their initial conditions.

The document is organized as follows. The second section offers a review of the literature. The third briefly describes the methodology, while the fourth section exposes our main results. The fifth section proposes policy actions to tackle the main challenges that AI poses in the labor market. The final section concludes.

## II. Literature review

In 1950, approximately 55% of Latin America's economically active population was employed in agriculture. However, forty years later, by 1990, this proportion had decreased to 26% (Infante and Klein 1991). By 2020, it had further declined to 14% (CEPAL 2024). The advent and widespread adoption of industrial machinery significantly reduced the demand for labour in the agricultural sector, prompting a shift of workers towards other productive sectors, such as services. The automation of many agricultural tasks resulted in the displacement of a substantial number of workers, yet simultaneously increased the productivity of those who remained, achieving higher output per hour. Workers who possessed or acquired the skills and abilities to utilise these machines benefited from their integration, whereas those who did not—primarily less-educated and older workers—were disproportionately affected by this technological progress.

Similarly, in the late 20th and early 21st centuries, the integration of computer services and robots brought about significant changes to routine jobs, both cognitive and physical, through automation. Acemoglu and Restrepo (2020) point that between 50% and 70% of the shifts in the wage structure in the United States from 1980 to 2016 can be attributed to relative wage declines among groups of workers specialising in routine tasks in industries undergoing rapid automation. In the U.S., they also show that the introduction of one additional robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%. Finally, in Europe, the penetration of robotics lowered both the relative wages and employment rates of the most exposed workers between 2006 and 2018 (Doorley et al. 2023). On the one hand, this may have resulted in less exposure of workers to dangerous routines, but it also presented a challenge for the labour market, where other areas had to absorb part of this unemployed mass.

While automation has replaced a significant portion of the workforce and affected their incomes, it also complements certain types of workers, increasing productivity in ways that lead to higher demand for labour and altering the types of jobs available (Autor 2015). In Germany, the adoption of frontier technologies by firms resulted in a decline in the proportion of routine jobs, a substantial increase in non-routine cognitive jobs, and a slight rise in non-routine manual jobs (Arntz et al. 2024).

Continuing with automation, in general, in occupations intensive in routine tasks, the adoption of ICT, the use of computers and the automation of processes through robotics has led to the replacement of low-skilled workers. Conversely, this shift has also resulted in a complementarity between technology and tasks that are abstract, creative, involve problem-solving, and require coordination, typically performed by highly skilled workers. As a result, low-skilled workers have reallocated their labour supply to service occupations, which are difficult to automate due to their heavy reliance on physical dexterity, flexible interpersonal communication, and direct physical proximity (David H Autor and Dorn 2013).

The process of automation has produced both winners and losers, leading to labour market "polarisation" in countries like the United States. In such cases, wage gains have disproportionately benefited individuals at the top and bottom of the income and skill distributions, while those in the middle have seen little benefit (David H. Autor 2015). However, the effects of automation on inequality remain inconclusive. For instance, Doorley and others (2023) found that the impact of automation on income inequality was limited in many European countries, largely due to fiscal and welfare policies.

While these findings are relatively consistent across developed countries, the situation is different in developing economies. Molina and Maloney (2016) show that labour market polarisation has not occurred in developing countries, although early signs of this trend can be observed in certain nations, such as China. Similarly, Hjort and Poulsen (2019) found that the introduction of high-speed internet in Africa led to increased employment, particularly in occupations requiring higher skills, while the impact on less-educated workers was smaller. In contrast, automation appears to affect informal workers disproportionately in developing economies. For example, Egana-del Sol, Cruz, and Micco (2022) demonstrated that the impact of automation on informal employees was three times greater than on formal employees in Chile after the pandemic. This finding is particularly significant for countries with high levels of informality, where the unequal effects of automation may exacerbate existing labour market vulnerabilities.

Finally, regarding gender differences in the levels of impact related to automation, findings diverge. Unlike Muro et.al (2019) who identify men as being more exposed, Egana-delSol et al (2022) report that the proportion of women at high risk is 21%, compared to 19% for men across four Latin American countries.

Despite extensive analyses on automation, various experts agree that the development of generative Artificial Intelligence (AI) exhibits significant differences from the processes observed in recent years. Generally, the features distinguishing AI from other automation technologies are its capacity to substantially expand the range of tasks that can be automated—extending beyond routine and non-cognitive tasks—and its potential to impact all occupational sectors, owing to its general-purpose nature (OECD 2023).

There is evidence of just incipient use of AI even in developed countries. For instance, research shows that in the US fewer than 6% of firms used any of the AI-related technologies (namely automated-guided vehicles, machine learning, machine vision, natural language processing, and voice recognition) though most very large firms reported at least some AI use (McElheran et al. 2024). Among dynamic young firms, AI use was highest alongside more-educated, more-experienced, and younger owners, including owners motivated by bringing new ideas to market or helping the community. We can argue that there is a relatively small version of this type of entrepreneur in middle income countries.

For instance, Webb (2020) indicates that exposure to AI is highest among highly skilled occupations, suggesting that AI will impact a demographic markedly different from those affected by software and robots. While low-skilled occupations are more exposed to robots and medium-skilled occupations to software, it is highly skilled occupations that face the greatest exposure to artificial intelligence. Furthermore, AI is significantly more likely to affect workers with higher educational attainment and older age profiles than these earlier technologies. Similarly, as noted in Cazzaniga et al (2024) unlike previous waves of automation—which had their strongest effects on medium-skilled workers—the risks of displacement associated with AI extend to higher-paid workers.

This point is particularly relevant because information technology has traditionally focused on automating routine tasks, with programmers specifying step-by-step instructions that can be translated into code. This approach largely affected mid-skilled jobs, thereby contributing to employment polarisation (Autor, 2015). By contrast, AI extends its scope beyond routine tasks to encompass more complex activities, which primarily involves highly skilled workers.

Nonetheless, certain studies (e.g. Frey & Osborne, 2017) highlight specific skills—such as persuasion and social intelligence—as potential bottlenecks to automation. This finding is broadly consistent with the Lassébie and Quintini (2022) that identifies negotiation, social perception, care and assistance for others, originality, and persuasion as skills that remain challenging to automate. Thus, while AI appears to have a greater impact on more complex activities, it also faces ongoing limitations.

A crucial aspect of analysing both the current and future impact of artificial intelligence (AI) adoption is to differentiate the channels through which it exerts its influence. Often, discussions focus on job exposure, suggesting that there is a certain likelihood of AI being integrated into these tasks; however, this does not necessarily equate to a direct impact on the exposed jobs. For instance, some roles may be entirely supplanted by AI once it assumes all the associated tasks. Conversely, there are positions in which AI only takes responsibility for a subset of tasks, thereby acting as a complement to the human worker and enhancing productivity. Furthermore, certain roles may undergo transformation due to AI's influence on specific tasks, leading to a restructuring of either the work itself or the broader occupational framework. Finally, entirely new roles may emerge in response to the proliferation of AI, potentially mitigating the unemployment effects precipitated by automation.

In this context, it is imperative for developing countries to consider the effects of artificial intelligence, given its potential as a catalyst for economic growth. Demombynes, Langbein and Weber (2025) conclude that middle-income countries experience a lower degree of exposure to AI compared to high-income countries, yet a higher degree than that observed in low-income countries. Thus, there exists a correlation between the level of exposure and national income levels. This relationship can be attributed, in part, to the differing composition of work across countries. In developing nations, there is a predominance of manual labour or roles that require personal interaction, which naturally limits the scope for AI integration. Additionally, inadequate access to essential infrastructure such as electricity and the internet further constraints exposure, particularly in low-income countries. The study also reveals notable demographic disparities. For instance, women are likely to experience higher levels of AI exposure in high-income and upper-middle-income countries, a trend that is similarly reflected among older workers. Such age-related differences, however, are not evident in emerging economies.

When examining the diverse regional scenarios, a closer look at Asia reveals distinct experiences between emerging economies and low-income countries, with AI impacting these settings in different ways. Although both economic groups may experience enhanced productivity, task complementarity is notably more pronounced in emerging economies, whereas low-income countries risk heightened unemployment. The IMF (2024) by combining exposure and skills needs methodologies proposed by Felten and others (2021) and Pizzinelli and others (2023) analises the situation for Asian countries. Their findings indicate that both the degree of exposure and task complementarity are higher in advanced Asian economies than in underdeveloped ones, thereby yielding greater productivity gains from AI. They further reveal that occupations at risk of displacement are primarily found within services, sales, and administrative support, while managerial, professional, and certain technical roles tend to be more complementary to AI. Similarly, it is noted that agricultural workers, tradespeople, and machinery operators are unlikely to be affected by AI at this stage. Sectoral differences are also apparent, with education, finance, information technology, health, and administration emerging as the sectors with the highest levels of worker exposure. Moreover, women face a greater risk of disruption from AI, as they are more likely to occupy roles in administrative support and services and sales, whereas men are disproportionately represented in trades, agriculture, and machinery operation.

For the Philippines, approximately one-third of occupations in the country are highly exposed to AI, although the vast majority are complementary to it (Cucio and Hennig 2025). Nonetheless, the Business Process Outsourcing (BPO) sector faces significant challenges, as it is one of the most vulnerable to automation. Despite representing a relatively small proportion of the workforce, the BPO sector contributes substantially to the nation's GDP. Consequently, AI could engender profound and complex effects on economies such as the Philippines, where extensive call centre operations and subcontracted roles might be supplanted by chatbots.

In contrast, the situation in Africa is markedly different. A substantial portion of its population is young and resides in rural areas—approximately 50%—with agriculture employing around 60% of the workforce, and a large segment of the working population are working in the informal sector. Given that emerging markets with a higher proportion of agricultural and informal workers tend to have a lower initial exposure to AI, it is anticipated that generative AI will have a delayed impact on African economies (Cazzaniga et al. 2024). Consequently, the levels of exposure, task complementarity, and the resultant productivity gains are likely to be distant, necessitating significant intervention to retrain and upskill the workforce and to narrow the existing digital divide (AUDA-NEPAD 2024). Additionally, another challenge faced by the continent is the low investment in research and development, which further complicates the adoption of this new technology (Azaroual 2024). Lastly, the AI investment in South Africa has a significant and adverse effect on low-skilled employment, highlighting the need to consider both the direct and indirect consequences of such policies (Giwa and Ngepah 2024) .

The scholarship for the Latin American case suggests that large language models (LLMs) would affect less than half of the population, with greater exposure among women, individuals with higher education, formal employees, and higher-income groups (Azuara Herrera, Ripani, and Torres Ramirez 2024) . This suggests a potential exacerbation of labour inequality in the region as a consequence of this technology's adoption. In addition Gmyrek and others (2024) demonstrate that, for instance, in Brazil and Mexico, workers in the highest income quintile are at least twice as likely to hold positions that would benefit from the use of generative AI. Furthermore, when adjustments are made for technology access, these disparities become even more pronounced.

With regard to job automation, the findings indicate a generally low level of automation; however, the impact is disproportionately concentrated among women and young people, a consideration that should be addressed by public policies. Moreover, some studies offer less optimistic or divergent perspectives. For instance, Bakker and others (2024) finds that approximately one quarter of jobs in Brazil, Chile, Colombia, Mexico, and Peru exhibit high exposure to AI yet low task complementarity, rendering them highly susceptible to automation—as observed in call centres. Conversely, around 20 percent of occupations, such as those in the medical field, display both high exposure and high task complementarity with AI, potentially resulting in significant productivity gains without displacing workers.

Finally, numerous studies concur that public policies concerning AI adoption and its effects on the labour market must account for the existing digital divide, which is typically more pronounced in regions such as Africa and in low-income countries. Ensuring the provision of essential services, such as reliable electricity, is also imperative. Additionally, it is advisable to prioritise the use of AI to augment human productivity rather than to drive automation. Encouraging AI applications that enhance human productivity, rather than replace workers, can help safeguard livelihoods and promote inclusive economic growth (Demombynes, Langbein, and Weber 2025). Furthermore, policymakers should concentrate on educational and training programmes to develop a digitally proficient workforce capable of harnessing AI technologies—a priority that is particularly relevant in emerging and developing markets, where relatively few jobs currently offer the potential for productivity gains through AI (IMF 2024). Finally, increasing investment in research and development, which remains comparatively lower than in more developed countries, is essential.

## III. Methods

This review employed a systematic search strategy to identify relevant articles published in preferably English, with an emphasis on those published since 2020. The primary objective was to explore the relationship between Artificial Intelligence (AI) and its impact on the labour market preferably in developing countries. However, due to evidence constraints, much of the available literature originates from developed economies—a reflection not of a research preference but rather of the greater volume of studies produced for those regions. To achieve this, keywords and search syntax were meticulously adapted to meet the specific requirements of each scientific database consulted.

The search terms were carefully selected to focus on the intersection of AI and employment dynamics within developing nations. Keywords included combinations such as "Artificial Intelligence," "AI," "labour market," "employment," "automation," "job displacement," "developing countries," “future of work,”, “income inequality,” and "emerging economies." These terms were adjusted according to the specifications of each academic search engine to optimise search results. Emphasis was placed on terms that directly relate to how AI technologies influence employment patterns in these countries.

Academic databases and search engines utilized in the selection process included Google Scholar and Scopus. These platforms were chosen for their extensive coverage of scholarly publications across multiple disciplines, ensuring a comprehensive capture of relevant literature.

In addition to traditional academic sources, grey literature was incorporated to enrich the review with diverse perspectives and the most current data. Grey literature sources comprised evaluations and reports from international organisations such as the United Nations, Inter-American Development Bank, the World Bank, and the International Monetary Fund.

The inclusion criteria for selecting documents were as follows: publications must be in English, focus on AI's impact on the labour market, and pertain specifically to developing countries within the specified time frame. Studies were excluded if they did not directly address the interplay between AI and employment or if they focused exclusively on developed nations. This ensured that the review remained relevant to the targeted context.

The synthesised data were analysed thematically to identify common patterns, trends, and gaps in the existing literature. The thematic analysis enabled a structured synthesis of findings, highlighting how AI influences labour markets in developing countries. This approach also facilitated the identification of areas requiring further research, thereby contributing to the advancement of knowledge in this field. In sum, this review aims to provide a comprehensive overview of the current state of knowledge on this critical subject.

Nevertheless, the disproportionate representation of data from developed countries highlights a significant methodological limitation. Preliminary findings indicate that AI is influencing labour markets globally, affecting both developed and developing economies. However, the scarcity of publications from developing countries suggests that the full extent and nuances of AI's impact in these regions may not be fully captured. Consequently, caution is warranted when extrapolating these findings to developing economies, and further research is essential to achieve a more balanced and globally representative evidence base.

Future research should aim to bridge this gap by fostering greater inclusion of studies from under-represented regions. Such efforts are essential for developing a more comprehensive and globally representative understanding of how AI is reshaping labour markets, ensuring that policies and strategies are effectively tailored to meet the needs of diverse economic landscapes.

## IV. Results

### A. Differences between countries

Although technological advancements tend to reach different parts of the world swiftly due to high levels of globalisation, their adoption typically proceeds much more rapidly in highly developed countries. The scope and pace of digital development contribute to unequal developmental trajectories among individuals and economies(APEC 2022). This observation is critical for understanding the impact of Artificial Intelligence (AI) on the future of work, as the technology will likely affect developed and developing countries in different ways. Indeed, there are growing concerns that AI could widen existing inequalities, enabling high-income countries to reap most of the benefits while leaving low- and middle-income countries behind (United Nations, 2024). Such disparities often stem from divergent levels of digital infrastructure, combined with sizeable populations that may lack essential resources—ranging from reliable electricity to water for cooling large-scale computing facilities.

Attewell (2001) distinguishes between primary and secondary digital divides. Primary divides refer to discrepancies in access to the internet, while secondary divides concern variations in how the internet is used. These distinctions are particularly pertinent in poorer and developing countries, where many individuals lack any internet access. According to the International Telecommunication Union approximately 63% of the global population used the internet in 2021. Meanwhile, according to GSMA (2021) estimates that around three billion individuals in low- and middle-income economies access the internet via mobile phones, representing one of the primary means of internet connectivity in these regions. Even among those with basic internet access, producing content or fully engaging in digital economies often requires specialised training, education, and employment opportunities—gaps that create significant differences in economic development and individual well-being (APEC 2022). These gaps are most pronounced among those from low-income countries.

Taken together, wealthier countries are more exposed to potential AI-driven automation in the labour market, yet they are also better positioned to harness the resultant productivity gains. In contrast, developing countries may initially experience relatively limited employment impacts due to insufficient digital infrastructure. However, this very limitation curtails their ability to capitalise on the productivity improvements enabled by AI (United Nations 2024).

Furthermore, low- and middle-income countries appear to have a proportion of jobs with significant potential for AI-driven enhancement that is broadly similar to that of high-income countries (World Bank 2024). The key difference, therefore, is primarily attributable to the prevailing digital divide. Nevertheless, certain occupations in low- and middle-income nations remain vulnerable to automation, particularly those outsourced by developed economies—such as call centre positions in the Philippines and India (Berg et al. 2023).

A further noteworthy study for Latin America is Egaña-delSol and Bravo-Ortega (2025).[2] Drawing on multiple data sources (including the World Bank's Skills Towards Employment and Productivity (STEP) survey, the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), and the two-digit International

[2] The countries considered for LAC were Bolivia, Colombia, Chile, Ecuador, El Salvador, Mexico and Perú.

Standard Classification of Occupations (ISCO-08)), the authors apply an expectation-maximisation algorithm (Ibrahim 1990) combined with automation risk estimates derived from Autor et al. (2003), Frey and Osborne (2017), Felten and others (2021) and Webb (2020). This methodology identifies the tasks most vulnerable to automation and calculates the estimated risk for each occupation.

In a nutshell, Egana-delSol and Bravo-Ortega's (2025) study reveals significant disparities in AI exposure across countries, gender, education, and age in Latin America compared to OECD countries, challenging conventional results on AI-based automation's labor market effects in developed economies (Felten and others, (2021); and Webb, (2020)).

Table 1 shows the correlation of skills and/or tasks using two different AI exposure indices. It is straightforward to see the differences across group of countries (i.e. LAC vs OECD), gender, level of education and age. For details on the estimations at country level see Egana-delSol and Bravo-Ortega's (2025). We will discuss this Table further in the following subsections.

**Table 1: Correlation of Skills/Tasks with AI Exposure Using Webb and Felten Indices**

| Skill/Task | Webb Index (LAC Males) | Webb Index (LAC Females) | Webb Index (OECD Males) | Webb Index (OECD Females) | Felten Index (LAC Males) | Felten Index (LAC Females) | Felten Index (OECD Males) | Felten Index (OECD Females) |
|---|---|---|---|---|---|---|---|---|
| **Management Skills** | 0.041*** | 0.084*** | 0.013* | 0.048*** | 0.050*** | 0.084*** | 0.034*** | 0.035*** |
| **ICT Skills** | 0.082*** | 0.057*** | 0.070*** | 0.050*** | -0.009 | 0.043*** | 0.049*** | 0.045*** |
| **STEM Skills** | 0.055*** | 0.055*** | 0.065*** | 0.069*** | 0.035** | 0.011 | 0.023*** | 0.006 |
| **Accounting Skills** | 0.068*** | 0.061*** | -0.051*** | -0.044*** | 0.007 | 0.030** | -0.061*** | -0.033*** |
| **Physical Tasks** | -0.082*** | -0.052*** | -0.036*** | -0.031*** | -0.091*** | -0.042*** | -0.093*** | -0.045*** |
| **Customer Contact** | -0.035*** | -0.012*** | -0.080*** | -0.060*** | 0.046*** | 0.026 | 0.042** | 0.022*** |
| **Self-Organization** | -0.006 | -0.026** | 0.017** | 0.002 | 0.003 | -0.010 | 0.005 | -0.025 |
| **Readiness to Learn** | -0.005 | -0.006 | 0.016** | -0.001 | -0.010 | 0.033** | -0.013 | 0.008 |
| **Autonomy in Work** | 0.011 | 0.016 | -0.007 | -0.051*** | 0.003 | 0.030* | 0.020 | 0.054** |
| **Repetitive Tasks** | 0.004 | -0.009 | 0.012 | -0.000 | 0.007 | 0.030** | -0.031 | -0.033 |
| **Critical Thinking** | 0.017 | 0.026** | -0.006 | -0.001 | 0.011 | 0.035** | 0.020 | 0.054** |
| **Medium-Level Education** | 0.047*** | 0.008 | 0.030*** | 0.021* | 0.040*** | 0.034** | 0.026 | 0.017 |
| **High-Level Education** | 0.189*** | 0.177*** | 0.048*** | 0.107*** | 0.269*** | 0.193*** | 0.181*** | 0.141*** |
| **Young Adults (18–25)** | -0.061*** | 0.003 | -0.063*** | -0.030** | -0.022 | -0.008 | -0.071*** | -0.023 |
| **Older Workers (25–40)** | -0.028*** | 0.006 | -0.019*** | 0.001 | 0.020 | -0.008 | -0.023 | -0.007 |

Note: Table taken from Egana-delSol and Bravo-Ortega (2025). Statistical significance levels are marked as follows: ***p < 0.01 (highly significant); **p < 0.05 (moderately significant); *p < 0.10 (weakly significant).

## B. Exposed occupations to AI

In addition to cross-country differences, numerous studies have attempted to estimate both the number and types of jobs likely to be affected by the use of Artificial Intelligence (AI). These studies generally adopt task-based models that identify the most common tasks within particular occupations, determining whether such tasks are (or are not) linked to AI (Acemoglu and Restrepo 2022). Through these models, two key considerations emerge: first, whether an occupation or sector is exposed to AI—defined by whether its tasks could be performed or complemented by this technology—and second, whether AI is expected to replace human workers, complement them, or remain in a grey area of uncertainty.

Cazzaniga (2024) based on exposure indices such as those introduced by Felten, Raj, and Seamans (2021) and Pizzinelli and others (2023), they find that in developed economies, approximately 60% of jobs are exposed to AI, of which half could be negatively affected while the other half could benefit from AI-related complementarities. They also show that exposure rates in emerging economies and low-income economies are 40% and 26%, respectively. Their findings indicate that professionals, managers, and technicians are most exposed.

A separate study focusing on developing Latin American economies is Gmyrek et al. (2024), which employs the model proposed by Gmyrek, Berg, and Bescond (2023). The authors find that between 30% and 40% of employment in Latin America and the Caribbean (LAC) is in some way exposed to generative AI. On the negative side, the proportion of jobs susceptible to automation represents 2% to 5% of total employment. On the positive side, the share of jobs that could benefit from productive transformation supported by generative AI consistently exceeds the proportion at risk of automation in all Latin American and Caribbean countries, ranging from 8% to 12% of total employment. However, the authors emphasise that realising these gains depends on bridging the digital divide still present in these economies relative to developed countries.

In terms of occupations with high risk of AI based automation, Egana-delSol and Bravo (2025) find results a diverse range of occupations for the countries in LAC. For the case of Mexico, for instance, they estimate that the top 5 occupation in term of AI exposure risk are science and engineering professionals, Health professionals, Teaching profesionals, public servants, and ICT professionals. These results are similar across countries. Moreover, these occupations clearly differ from the more routine, less skillful occupations typically found in the pre-AI automation literature (i.e. (Egana-delSol et al. 2022). In addition, when looking the occupations with larger number of workers under high risk, they find that the top 5 occupations are Sales, Plant operators, cleaners and helpers, food processing, and mining, construction, and manufacturing workers, for the case of Mexico as well.

Moreover, the same authors reveal for the case of sample of LAC countries that higher AI exposure is linked to significant employment growth but has an unclear impact on wages. Using Webb's methodology, one unit of extra AI exposure corresponds to a 1.29% rise in employment, while Felten's measure shows a 0.6% increase—both statistically significant. However, wage effects remain small and statistically insignificant, suggesting that AI adoption may drive job creation and task reallocation, but its influence on wage growth is uncertain.

These findings imply that while AI adoption leads to employment expansion, it does not necessarily translate into higher wages, possibly due to the relocation of workers to occupations with higher complementarity with AI, without proportionally increasing labor income. This highlights the need for targeted policy interventions to ensure that AI-driven employment growth also contributes to increase in wages due to the increase of labor productivity.

Lastly, Benitez and Parrado (2024), employing a similar approach and developing a new index of exposure (the Generated Index of Occupational Exposure, or GENOE), use labour data from the United States and Mexico to show that occupations have a 28% probability of being potentially affected by AI within the next year, rising to 38% in the next five years and 44% in the next ten. Extrapolating these findings worldwide, they note that telephone operators, credit authorisers, travel agents, and similar roles are among those most exposed to this emerging technology.

### C. Skills of individuals exposed to Artificial Intelligence

Focusing on those occupations most exposed to automation through artificial intelligence, recent evidence indicates that administrative jobs involve the highest proportion of tasks with medium or high automation potential (Berg et al. 2023). This category encompasses administrative support roles and positions responsible for typing and data entry, where over 50% of tasks may be automated (World Bank 2024).

As Table 1 indicates, their findings highlight pronounced gender differences, particularly in Latin America, where women in high-level managerial and ICT roles face greater AI exposure than men. This pattern suggests that even skilled female-dominated occupations remain susceptible to ai-based automation, exacerbating existing gender inequalities.

The findings indicate that, unlike pre-AI automation—which negatively correlates with high levels of education and physical skills—AI exposure is positively correlated with higher levels of education, as well as with ICT and STEM skills, but negatively correlated with younger workers (aged 18–25). Comparing OECD countries with those in Latin America and the Caribbean, the effects are found to be larger in the latter. In OECD countries, but not in LAC, physical skills correlate negatively with AI exposure. In both regions and for both earlier automation and AI, contact with clients shows a negative correlation, suggesting that customer-facing tasks might be a bottleneck.

Table 1 shows that physical tasks remain one of the least automatable categories, showing strong negative correlations with AI exposure in both LAC and OECD. In LAC, men working in physically intensive jobs have an AI exposure of -0.082*, while women show a similar trend at -0.052***. In OECD countries, the negative correlation is even stronger for men (-0.036***) and women (-0.031***), indicating that these roles continue to be less susceptible to automation. These findings suggest that manual labor remains a bottleneck for AI-driven automation, likely due to the complexity of physical dexterity and the need for human adaptability in non-repetitive tasks.

Similarly, customer-facing roles appear resistant to AI displacement, as evidenced by strong negative correlations in both regions. In LAC, customer-facing roles decrease AI exposure for men (-0.035*) and women (-0.012***), while in OECD countries, the negative effect is even greater (-0.080*** for men and -0.060*** for women).** These results indicate that AI has not yet reached the level of sophistication required to fully replace human interaction in client-facing occupations, reinforcing the importance of soft skills in labor market resilience.

Moreover, STEM skills are positively correlated with AI exposure in both LAC and OECD, suggesting that even high-skilled technical roles are increasingly vulnerable to automation. The results show a consistent AI exposure increase across men and women in both regions, though the effect is slightly stronger in LAC (0.055***) than in OECD (0.065*** for men and 0.069*** for women). This pattern aligns with findings that AI technologies are primarily affecting knowledge-based tasks that require technical expertise.

ICT skills also increase AI exposure across all groups, but the impact is particularly strong for women. In LAC, women with high ICT skills face an AI exposure of 0.057*, while in OECD countries, the effect is similarly significant at 0.050*. These results suggest that highly technical roles, often requiring programming, data analysis, or digital competencies, are at greater risk of automation regardless of region.

Another striking difference is observed in accounting skills, which exhibit opposite correlations across regions. In OECD countries, accounting skills reduce AI exposure (-0.051*), indicating that these roles might involve more strategic, analytical, or regulatory aspects that are harder to automate. However, in LAC, accounting skills are strongly associated with increased AI exposure (0.068*), possibly reflecting that accounting tasks in the region remain highly routinized and therefore more susceptible to AI-driven automation.

By contrast, while roles requiring greater levels of knowledge and abstraction also face some degree of AI exposure, this tends to be partial. As a result, AI is more likely to act as a productivity enhancer in these occupations, rather than fully automating tasks and displacing workers (Berg et al. 2023). Lastly, and distinct from earlier automation processes, agricultural and craft-based jobs are among the least susceptible to automation, with fewer than 10% of their tasks considered automatable (Banco Mundial 2024).

### D. Education of individuals exposed to Artificial Intelligence

With respect to the educational level of those most exposed to AI, various estimates show that highly educated workers—generally those with tertiary qualifications—who are employed in the formal sector and earn relatively higher incomes have greater opportunities to engage with this technology (Gmyrek et al. 2024). Accordingly, university-educated workers are also better positioned to transition from jobs at risk of displacement to roles that exhibit strong complementarities with AI (Cazzaniga et al. 2024).

Egana-delSol and Bravo-Ortega's (2025) also finds that, contrary to traditional economic models, higher educational attainment in Latin America correlates with increased AI exposure, likely due to sectoral dynamics that make high-skilled roles more vulnerable to AI-based automation. This calls into question the assumption that education alone shields workers from technological disruption, emphasizing the need for curriculum adaptation and continuous reskilling.

In both LAC and OECD countries, higher education is strongly correlated with AI exposure. In LAC, men with high education levels experience an AI exposure of 0.189*, while women face an even higher risk at 0.177*. Similarly, in OECD countries, higher education significantly increases AI exposure for both men (0.048***) and women (0.107***).** These findings indicate that highly educated workers are more likely to be employed in roles that AI can automate, highlighting the need for reskilling programs that focus on adaptability rather than just educational attainment.

In sum, this contrasts with the earlier wave of automation, which most adversely affected routine-based skills. In that context, middle-class workers primarily occupied positions susceptible to software-driven replacement, leading to a shock for this group and triggering labour market polarisation. By contrast, as AI now affects people with higher educational attainment—who typically command higher incomes—it is unlikely to yield the same polarising consequences.

Lastly, when examining the possibility of occupational transitions linked to holding a tertiary degree, workers without university education are shown to face a substantially higher risk of downward mobility, a trend relatively independent of their current occupations (Cazzaniga 2024). Their vulnerability to automation is therefore heightened, as they lack the capacity to move into less exposed roles. This stands in contrast to workers with university-level education, who tend to follow “upward” career paths and possess greater potential for occupational retraining.

### E. Age of individuals exposed to AI

Another important factor influencing workers’ exposure to AI—and the potential effects thereof—is age. Indeed, older workers may be particularly susceptible to AI-driven transformations (Cazzaniga et al. 2024). This vulnerability may stem, in large part, from their reduced capacity to adapt to new technologies, increasing their risk of being replaced. They may also have less flexibility in moving from high-exposure roles to those involving lower exposure—an issue often more pronounced for older workers with higher education.

Conversely, for more experienced (and therefore older) individuals in supervisory or managerial roles, AI can facilitate increased productivity and serve as a valuable complement in areas where automation poses a comparatively lower threat.

Regarding age group and AI risk, Egana-delSol and Bravo-Ortega (2025) suggest that younger workers (ages 18–25) are less exposed to AI across all regions, though the effect is more pronounced in LAC (-0.061*) than in OECD (-0.063*** for men and -0.030** for women).** This suggests that younger workers may be employed in less structured or adaptable roles, which are currently less susceptible to AI-driven automation. In contrast, for older workers (ages 25–40), the correlations are mostly insignificant, though in LAC, men face a slight negative correlation (-0.028*)**, while in OECD, the effect is minimal.

These findings indicate that early-career workers may have a temporary advantage in avoiding AI disruption but may face increasing risks as they advance into roles with higher automation potential.

By contrast, younger workers tend to face a higher degree of job automation, particularly in finance, insurance, and public administration (Gmyrek et al. 2024). Nonetheless, they often possess greater adaptability, as their stronger familiarity with technology enables them to develop the requisite skills through training with relative ease.

### F. Gender of individuals exposed to AI

Another important source of inequality in the development and use of Artificial Intelligence (AI) concerns gender. First, women are more concentrated in sectors that are particularly susceptible to AI-driven automation, such as finance, insurance, and public administration (Gmyrek et al., 2024). Within these sectors, women often hold administrative and office-based positions, rendering them especially vulnerable to AI-related displacement (Benitez and Parrado, 2024). Second, gender gaps originating in the education system can also lead to uneven AI outcomes, as women tend to be underrepresented in STEM fields, which themselves face a high degree of AI exposure (Egana-delSol and Bravo-Ortega 2025). This imbalance could have negative implications if AI proves complementary to skills typically taught in STEM disciplines. Lastly, a significant digital divide remains—particularly in Latin America—where many workers do not use computers in their jobs (United Nations, 2024). This divide is even wider among women: in 2019, approximately 55% of men used the internet, compared with just 48% of women (ITU 2020).

In particular, the results from Egaña-delSol and Bravo-Ortega (2025) indicate significant gender disparities in AI exposure, particularly in Latin America and the Caribbean (LAC). Women with high management skills face substantially greater AI exposure in LAC (0.084***) compared to their male counterparts (0.041***). This suggests that female-dominated managerial roles in LAC may involve more structured and routinizable decision-making processes that AI can automate. In contrast, in OECD countries, the effect of management skills on AI exposure is more balanced, with *both men (0.013) and women (0.048***) experiencing increased risk, though the impact remains lower than in LAC**.

G. Inequality

As previously noted, not only are some occupations potentially more susceptible to the impacts of Artificial Intelligence (AI) than others, but workers' characteristics also play a crucial role, revealing disparities that may exacerbate inequality. In particular, the adoption of AI could intensify income inequalities by disproportionately affecting low- and middle-income workers (Benitez and Parrado 2024), compared with their higher-income counterparts.

Furthermore, nearly half of the occupations that could benefit from AI-driven expansion are constrained by digital skill deficits, which hinder the realisation of their full potential. Specifically, 6.24 per cent of the jobs held by women and 6.22 per cent of those held by men are adversely affected by these deficiencies (Gmyrek et al. 2024). In addition, the potential complementarity of AI is positively correlated with income, thus contributing to growing inequality (Cazzaniga et al. 2024).

These disparities manifest not only within individual countries but also across national boundaries. For instance, the digital divide is a significant gap between developed nations and those of medium or low development. Similarly, the gender gap tends to be more pronounced in less developed countries. Recent data from the APEC region indicate that women use the internet less frequently than men in all economies—except the United States—with the widest gaps recorded in Peru, Indonesia, and Malaysia (OECD 2019; ITU 2020). In this sense, AI has the potential to exacerbate inequality both within and among countries.

### H. Others

An avenue worth exploring is that while AI affects jobs in developing countries (such as call-centre roles), it can also have a positive impact by stimulating investment in the infrastructure necessary for its use—data centres, for instance—or by creating remote employment opportunities in more advanced economies. Such developments could capitalise on AI's ability to overcome language barriers and reduce labour costs. For these possibilities to materialise, however, countries must provide favourable conditions for investment and equip their populations with the requisite skills to seize emerging opportunities.

At the same time, despite existing gaps in technology and resources, AI adoption may prove even more transformative for poorer countries, precisely because they are further removed from the technological frontier. By effectively harnessing AI, these countries could unlock economic growth and accelerate convergence with higher-income economies.

Finally, both workers and employers report that AI can alleviate tedious and hazardous tasks, thereby enhancing worker engagement and physical safety. Nevertheless, there are also indications that AI-driven automation of simpler tasks may leave workers in fasterpaced, more intense roles (OECD 2023). As such, the way in which workers respond to these new technologies—alongside limits on the scope of AI implementation—warrants careful consideration. Furthermore, the degree of regulation or deregulation surrounding AI will likely play a pivotal role in determining how opportunities are realised and the extent to which outcomes differ among countries with varying policy frameworks.

## V. Policy proposals

The transformative potential of AI continues to reshape global labour markets, public services, and the broader economic landscape. As AI-driven technologies grow increasingly sophisticated, many workers fear displacement and diminished job satisfaction, while gaps in infrastructure and digital literacy risk leaving entire communities behind. At the same time, the rapid expansion of AI offers opportunities to enhance social protection systems, spur productivity, and modernise traditional vocational training approaches. Policymakers thus face the dual challenge of maximising AI's potential for social and economic progress while minimising the inequalities it may exacerbate, particularly for mid-level qualified employees or those residing in regions plagued by insufficient internet access. In response, governments, international organisations, and private-sector actors have begun introducing measures designed to promote inclusive, human-centred AI adoption. The success of these initiatives, however, depends on striking an appropriate balance between fostering innovation and safeguarding the fundamental rights and welfare of workers worldwide.

This section explores key dimensions of AI's impact on employment and policy responses designed to address them. First, it examines workers' concerns, focusing on anxieties surrounding job security and life satisfaction, as AI-driven disruptions transform traditional roles. Next, it underscores the importance of access to internet services, emphasising how digital infrastructure can enable or hinder AI adoption and perpetuate existing divides, especially in developing countries. Attention then shifts to social protection, highlighting how governments can harness AI to improve service delivery while mitigating the risks of technological exclusion. Building on this, the section addresses labour market formalisation, illustrating how regulations, collective bargaining, and antitrust enforcement can protect workers from wage suppression and precarious employment arrangements. It subsequently discusses vocational training, emphasising the need for comprehensive programmes that equip individuals with AI-focused skills. Finally, it examines worldwide actions and initiatives, illuminating global efforts to harmonise tax policies, foster equitable AI governance, and empower public institutions.

### A. Workers' Concerns

Recent evidence underscores the growing apprehension amongst workers regarding the potential impact of AI, particularly Generative AI, on their future employment prospects. Surveys suggest that a significant proportion of employees fear job loss as AI systems become increasingly sophisticated, eroding traditional roles and responsibilities (Gmyrek et al. 2024). Beyond mere job security, the advent of AI also appears to be correlated with diminished life satisfaction. Indeed, workers exposed to AI report lower life satisfaction, with an estimated difference of 0.04 standard deviations relative to those not exposed (Giuntella, Koenig, and Stella 2023). This figure, while seemingly small, amounts to approximately 16% of the positive effect of holding a university degree on life satisfaction, or around 13% of the negative effect of being unemployed.

In light of these trends, policymakers face the challenge of designing strategies that both assuage employees' concerns and ensure a balanced distribution of AI's benefits. One potential approach involves promoting lifelong learning and continuous upskilling. State-subsidised training programmes can equip workers with the competencies needed to adapt to shifting demands, mitigating the threat of redundancy and easing anxieties surrounding obsolescence. Furthermore, targeted interventions that address the unique vulnerabilities of mid-level qualified workers, who have experienced more pronounced declines in job satisfaction since 2015, could help stabilise employment outcomes such as the case of Germany (Giuntella, Koenig, and Stella 2023).

Encouraging open dialogue between employers, employees, and government bodies is equally vital. Through structured frameworks for employee consultation, both parties can establish fair guidelines for the integration of AI technologies, ensuring that workers' concerns are accounted for in organisational decision-making. Additionally, public awareness campaigns may serve to clarify misconceptions around AI, thus fostering a more informed and less fearful workforce, especially for largely exposed occupations to AI. By combining these policy measures, governments can proactively address the implications of AI on life satisfaction and job security, helping to ensure that the technological revolution delivers broad-based benefits rather than compounding existing insecurities. In OECD countries where consultations have taken place, there is a discrepancy ranging from 11 percentage points in the manufacturing sector to 17 percentage points in the financial sector, with workers expecting that the utilisation of artificial intelligence in performing their tasks will result in higher wages. Moreover, employers are more inclined to report that the adoption of artificial intelligence confers greater benefits in terms of working conditions and productivity. Finally, the primary concerns raised by workers pertain to skills and training, which have immediate implications for the development of new guidelines (Lane, Williams, and Broecke 2023).

### B. Access to internet services

Ensuring equitable access to high-speed internet services is a central priority for policymakers seeking to harness the full potential of AI. While AI-driven technologies offer considerable promise for enhancing productivity and innovation, digital deficiencies continue to inhibit these benefits in almost half of the positions that stand to gain most (Gmyrek et al. 2024). This reality highlights the urgent need for targeted interventions aimed at reducing disparities in connectivity infrastructure and promoting the widespread availability of reliable internet.

A key driver of technology adoption lies in the existence of robust, high-speed internet networks, which serve as the backbone for implementing advanced digital tools (Arntz et al. 2024). In practice, governments can achieve such connectivity objectives by investing in the expansion of broadband coverage, offering subsidies to lower access costs, and introducing regulatory frameworks that encourage competition among service providers. Through these measures, it becomes possible to foster an environment in which businesses, public institutions, and households alike can seize the opportunities afforded by AI. For instance, Chile has recently enacted legislation declaring internet access a public service. Consequently, it qualifies for demand-side subsidies, and internet providers are mandated to ensure comprehensive coverage within their designated service areas. Moreover, the legislation authorises the provision of internet services via cooperatives and establishes mechanisms for the regulatory oversight of the service.

Nevertheless, policy efforts to enhance digital infrastructure must also recognise the sizeable internet and electricity gaps that persist in less developed countries. Indeed, limited connectivity not only hinders the immediate uptake of cutting-edge technologies but also perpetuates a widening digital divide, leaving vast segments of the population unable to benefit from emerging innovations (Berg et al. 2023). In such contexts, policies tailored to rural and underserved areas—ranging from public-private partnerships to community-based digital education programmes—can help mitigate infrastructure and knowledge barriers. Moreover, linking internet expansion to broader initiatives in energy provision ensures that even the most remote communities can effectively participate in the digital economy.

### C. Social protection

As AI technologies advance at an unprecedented pace, their impact on social protection frameworks becomes increasingly evident. On one hand, AI promises to enhance the efficiency and accessibility of benefits, including more targeted assistance and faster disbursement of crucial aid (OECD 2024b). By matching individuals' profiles with available forms of support, social security agencies can proactively inform eligible citizens of programmes they might otherwise overlook, thereby expanding the reach of essential services. Automation further streamlines benefits administration by eliminating human error and reducing administrative burdens, enabling social protection agencies to allocate more resources towards improving service coverage and quality (OECD 2024a). For instance, Togo has implemented NOVISSI, an unconditional cash transfer programme that employs machine learning and artificial intelligence to prioritise impoverished rural populations during emergencies, particularly in contexts lacking a robust social registry and shock-responsive social protection delivery mechanisms (Lawson et al. 2023).

Similarly, Brazil utilises AI to detect fraud within its largest cash transfer programme, Bolsa Família, and its corresponding social registry (CadÚnico). Finally, Korea extensively applies AI to identify fraud and misuse within its public health insurance system, leveraging existing data on the utilisation of health services and insurance claims to flag suspicious cases (OECD 2024b).

On the other hand, the advent of AI raises critical distributional questions. The way AI property rights are defined and how redistributive fiscal policies are structured will largely determine whether productivity gains sufficiently offset potential labour market disruptions (Cazzaniga et al. 2024). By regulating ownership and profit-sharing mechanisms for AI innovations, policymakers can channel part of the resultant economic gains into social programmes designed to protect workers from sudden job displacement and income shocks. This approach becomes especially relevant in contexts where automation can shift the distribution of returns in both labour and capital markets, as some firms may accumulate substantial profits while others fall behind (Bastani and Waldenström 2024).

Collective bargaining and social dialogue also play a vital role in guiding a fair transition to AI-driven workplaces (OECD 2023). By engaging employees and employers in discussions on wage-setting, skills development, and working conditions, policymakers can help ensure that AI tools do not exacerbate existing power imbalances (Berg et al. 2023). This inclusive dialogue, ideally undertaken in anticipation of upcoming technological shifts, helps align AI's potential efficiencies with overarching goals of equity and fairness. Similarly, strengthening social safety nets and offering continuous training or upskilling opportunities to workers most at risk of displacement serves as a cornerstone of inclusive labour markets (Cazzaniga et al. 2024). For example, trade unions in the US and Germany have been raising concerns about the use of AI on surveillance introducing power imbalances between workers and employers (Krämer and Cazes 2022). Fiscal interventions grounded in progressive taxation can raise the revenue needed for such initiatives, ensuring that those most likely to benefit from AI innovations contribute proportionately to collective welfare.

Although taxation can partly compensate for wage declines, direct benefit transfers and robust welfare systems have proven particularly effective in cushioning the adverse impacts of automation on total household disposable income (Doorley et al. 2023). This underscores the importance of reinforcing unemployment insurance, expanding universal basic services, and creating targeted support programmes to protect vulnerable populations from sudden earnings losses. Equally vital is the need for robust data governance and specialised technological infrastructure to implement AI solutions securely and transparently, thereby preventing potential breaches of public trust, such as the case of e-government developed by Estonia (OECD 2024b).

Finally, the introduction of AI-based solutions must be designed to avoid creating new forms of exclusion. Individuals with limited digital access or insufficient digital literacy risk being marginalised from automated services, thus widening the very gaps these technologies aim to close. Policymakers and social protection agencies can mitigate this risk by embedding inclusive strategies within AI initiatives—ensuring that all segments of society benefit equally (OECD 2024b). By doing so, they will not only foster public confidence in AI-driven social protection but also contribute to more equitable, resilient, and inclusive welfare systems(OECD 2024a). There are instances where AI-based procedures have resulted in the exclusion of households from social benefits. For example, in the Netherlands, households have been categorised as fraudsters, while in

Sweden, errors in the automated decision-making algorithms have led to the rejection of unemployment benefits for eligible individuals. Similarly, in Australia, there have been cases of income misreporting among households from ethnic minority backgrounds (Wagner, Ferro, and Stein-Kaempfe 2024).

### D. Labour market formalisation

Recent scholarship highlights how the widespread adoption of AI and automation can have uneven repercussions on labour markets, particularly when firms wield monopsony power. Under such conditions, automation exerts downward pressure on both the number of jobs available and the wages of the remaining workforce, effectively amplifying the negative consequences of technological change (Azar et al. 2023). This dual impact underscores the importance of formulating robust policies that foster labour market formalisation to mitigate the risks posed by automation while safeguarding workers' rights and livelihoods.

A first policy priority is to enhance legal frameworks and institutional structures that support formal employment arrangements. By mandating written contracts, enforcing transparent remuneration practices, and requiring the provision of social insurance, governments can reduce precarious work patterns and strengthen workers' bargaining positions. These measures help ensure that, even in the face of technological disruption, employees retain a baseline of security. In addition, clearly defined contractual obligations can limit the capacity of monopsonistic firms to unilaterally dictate wages when labour demand declines due to automation. However, there exists a threshold beyond which rising formal labour costs incentivise greater reliance on technology, thereby reducing the need for workers and lowering the firm's operating expenses

A second approach involves actively promoting collective bargaining and worker representation. Where employees can negotiate wages and working conditions collectively, the scope for monopsonistic exploitation diminishes considerably. Collective negotiations allow workers to press for fair compensation even as automation substitutes certain tasks, thereby curbing downward pressure on wages. Governments might encourage such arrangements through legislation that sets clear guidelines to ensure fair negotiations to adjust the impacts on wages in the formal sector, especially in mid-skilled workers and occupations. Lane, Williams and Broecke (2023) found that, for developed OECD member countries (Austria, Canada, France, Germany, Ireland, the UK, and the United States), companies that conducted consultation sessions with workers regarding AI achieved better adoption and utilisation of this technology, as well as more positive perceptions concerning safety and health, compared to those that did not engage in such processes. Moreover, the results indicate that workers using AI are more likely to report that it improved their performance and working conditions when their companies consulted with them or with worker representatives prior to adopting new workplace technologies. Conversely, workers' organisations ought to harness digital technologies to mobilise and organise labour. This approach should involve enhanced engagement with informal workers and the adoption of more inclusive organising strategies (ILO 2019). For example, in Germany, trade unions have actively engaged in debates on AI regulation, thereby fostering cooperative strategies between management and works councils concerning both the implementation and oversight of AI technologies (Krzywdzinski, Gerst, and Butollo 2023).

Antitrust enforcement also emerges as a key factor in mitigating the adverse consequences of automation. By scrutinising mergers and acquisitions that risk consolidating excessive labour market power, policymakers can preserve competitive conditions, thus counteracting the wage suppression that automation may induce (Azar et al. 2023). Simultaneously, active labour market policies—such as re-skilling programmes and job-search assistance (Solutions for Youth Employment (S4YE) 2023) or Digital Talent for Chile (Neilson, Egana-delSol, and Humphries 2024)—can assist displaced workers in securing alternative routes to gainful employment, thereby reducing periods of unemployment and alleviating downward pressure on wages.

On one hand, artificial intelligence is being employed as a tool for matching labour market demand and supply on a skills-based approach within public employment services in countries such as Latvia, Korea, Spain and Greece (Brioscú et al. 2024). On the other hand, Singapore has implemented the SkillsFuture initiative to mitigate the disruptive impact of artificial intelligence by offering training specifically tailored to AI technologies. SkillsFuture is a government-led programme that promotes lifelong learning and skill development, thereby equipping workers with the competencies necessary to adapt to rapid technological changes (International Monetary Fund 2024)

### E. Vocational training

The rapid expansion of AI technologies has created a pressing need for enhanced vocational training programmes tailored to address emerging skills gaps. While many firms report offering AI-related training, the persistent shortage of qualified personnel remains a primary obstacle to wider adoption and effective implementation (OECD 2023). This skills deficit not only undermines productivity and competitiveness but also impedes more inclusive labour market outcomes, as certain occupations become increasingly susceptible to technological displacement. By designing and funding comprehensive vocational training initiatives, policymakers can better equip the current and future workforce to harness the transformative potential of AI while mitigating adverse consequences for vulnerable and exposed occupational groups.

One key rationale for focusing on vocational training lies in its demonstrable impact on employment prospects. Research indicates that individuals with AI-related skills enjoy improved odds of receiving interview invitations, as well as higher hourly wages (Drydakis 2024). This advantage not only reflects an evolving demand for AI competencies but also underscores the broader value of educational capital in labour markets subject to technological change. Considering these findings, strategies aimed at integrating AI modules into existing technical and vocational curricula can help bridge the gap between conventional training models and the rapidly shifting demands of the digital economy.

To optimise these efforts, governments should pursue a two-pronged approach. First, advanced and emerging market economies ought to invest in AI innovation and integration while establishing robust regulatory frameworks that foster ethical and inclusive technological development (Cazzaniga et al. 2024). By doing so, policymakers can encourage businesses to collaborate with educational institutions to develop targeted training modules and support apprenticeships, thereby ensuring that learners acquire the specific skills most in demand for the local labour market. This collaboration could include financial incentives, public-private partnerships, or scholarship schemes aimed at promoting enrolment in AI-focused vocational training.

Second, in less prepared emerging and developing market economies, priority should be given to building foundational infrastructure and cultivating a digitally skilled workforce (Cazzaniga et al. 2024). These efforts involve expanding reliable internet access, ensuring stable electricity supplies, and creating local ecosystems of innovation that can nurture newly trained AI professionals. Vocational schools in these regions must be equipped with up-to-date facilities and supported by well-trained educators capable of delivering relevant, high-quality programmes. International cooperation and development assistance could play a critical role here, complementing domestic efforts through technical expertise and targeted investment.

### F. Worldwide actions and initiatives

One prominent concern arises from the prospect of shifting tax burdens: as AI reshapes economic activity, governments may find it necessary to shift taxation away from labour and towards capital in order to sustain revenue for public investment and redistribution (Bastani and Waldenström 2024). In the event that AI-driven technologies also facilitate greater international mobility of both labour and capital, the coordination of tax policies across borders becomes increasingly pressing. Without such coordination, countries risk engaging in a race to the bottom, undermining their collective capacity to finance essential social protection programmes.

Recognising these challenges, various international organisations and national governments have proposed collaborative strategies aimed at shaping a fair and inclusive AI ecosystem. Among these proposals is a call for enhanced international cooperation and knowledge exchange, underpinned by a unified methodology for measuring AI's economic and social impact (United Nations 2024). Such cooperation extends to the establishment of joint training initiatives and partnerships between countries, designed to foster innovation and ensure that AI infrastructure and benefits are distributed equitably. Alongside these collaborative measures, recommendations for the continuous education and training of affected workers underscore the importance of upskilling and reskilling, ensuring that the workforce remains prepared for the rapidly evolving demands of AI-intensive industries and reduce potential losses on employment and wages.

Governments and intergovernmental agencies also acknowledge the need to regulate AI in a manner that preserves competition and protects vulnerable groups. The potential for AI to reinforce the market dominance of major technology firms, displace lower-skilled occupations, and exacerbate income inequality is a growing concern (World Bank 2024). Regulatory responses, however, must be carefully balanced. While fragmented or overly rigid regulations risk stifling innovation and encouraging regulatory arbitrage, overly permissive regimes may fail to address emerging ethical dilemmas or labour market inequalities (World Bank 2024). Striking a balance between these extremes is crucial for fostering an environment that rewards responsible innovation.

Equally important is the integration of AI solutions into public institutions, which can significantly enhance the delivery of public services and support effective governance (World Bank 2024). For example, AI-driven approaches have the potential to modernise social protection systems by automating administrative tasks, improving targeting mechanisms, and reducing errors in the allocation of benefits (OECD 2024a). Yet, to realise these gains without compromising the welfare of those likely to be displaced by automation, policymakers must prioritise inclusive, human-centred design and ensure that new technologies are supported by robust data governance frameworks.

## VI. Conclusions

The findings presented here underscore the multifaceted implications of technological change for the labour market, particularly when comparing the effects of traditional automation to those arising from AI. In the literature, automation has chiefly been characterised by its strong focus on routine and non-cognitive tasks, exerting a polarising effect on the employment landscape by reducing real wages for mid-tier workers and prompting broader labour market restructuring, especially in developed economies. This dynamic has contributed to the hollowing-out of middle-skill occupations, as routine tasks amenable to standardisation and mechanisation are increasingly automated. By contrast, AI appears to be reshaping a distinct segment of the labour market—one that relies on non-routine cognitive tasks, creative aptitudes, and complex problem-solving skills. Consequently, AI's influence is beginning to permeate roles once viewed as insulated from automation processes.

A key insight emerging from recent studies is that non-routine cognitive jobs are now increasingly exposed to AI's expanding capabilities. Although there remains limited but growing evidence of outright job displacement in these domains, clear indications suggest that tasks traditionally performed by humans are being replaced or substantially transformed. In many highly skilled occupations, for instance, AI-based systems can execute routine components of knowledge-intensive tasks, thereby freeing workers to concentrate on higher-value or more cognitively challenging responsibilities. For instance, Lassebie and Quintini (2022) reinforces this perspective, illustrating that individuals with advanced digital competencies, robust cognitive skills, and the capacity for creative thinking or social intelligence can employ AI as a complementary resource, optimising task performance and progressing into more innovative or managerial roles.

In this sense, the extent of task reorganisation depends largely on workers' skill profiles and the enabling infrastructure.

Furthermore, it is observed that exposure will also depend on the characteristics of the workers. These non-routine jobs target a segment of workers with more education and older age, who will be more exposed (Egana-delSol and Bravo-Ortega 2025). The ability to complement the use of this technology and to retrain to other less exposed areas will be key to successfully overcome this exposure and possibility of job automation. With this, the digital divide and its gender component is also an important attribute for the use of this technology. Making it compatible to have access and thereby take advantage of the benefits of using AI, reducing the gap in digital infrastructure that exists, but at the same time under a resilient labor system due to the possibilities of automation, is a goal that must be pursued.

Against this backdrop, upskilling and reskilling initiatives, especially those focused on AI-related fields, emerge as pivotal for mitigating the adverse consequences of automation and AI deployment. Vocational training programmes that emphasise creative thinking, advanced problem-solving skills, and digital literacy offer strategic pathways for enhancing employability in a rapidly evolving technological landscape. By fortifying the overall skill base, such initiatives help mitigate the risks of displacement and promote a fairer allocation of AI's benefits. In addition, continuous professional development not only supports individual workers but also bolsters local economies by fostering innovation and productivity. Equipping the workforce with AI competencies allows them to transcend routine tasks and embrace emerging opportunities across various industries.

Nevertheless, successfully equipping workers with AI-relevant skills relies on addressing the broader digital divide. Policymakers must prioritise infrastructural improvements in regions plagued by unstable electricity supplies, patchy internet connectivity, and inadequate technological resources. In the absence of sustained efforts to resolve these foundational shortcomings, even the most comprehensive upskilling programmes are likely to fall short. Reducing the digital gap, therefore, constitutes not merely an economic imperative but also a crucial objective for human development, as it promotes equitable participation in the digital economy and curbs the entrenchment of existing inequalities.

Furthermore, AI's growing capacity to influence non-routine, cognitive tasks calls for innovative policy responses that extend beyond traditional sectoral boundaries. Governments and other institutions can no longer focus solely on interventions tailored to the effects of automation on routine-based occupations; they must instead devise integrative strategies that consider how AI might transform realms as diverse as healthcare, education, financial services, and public administration. Simultaneously, policymakers should adopt inclusive perspectives to forestall labour market polarisation associated with AI's rapid advancement, ensuring that workers from a range of educational and socioeconomic backgrounds do not become marginalised. From a global standpoint, there is an equally urgent need for multilateral coordination surrounding tax policies, intellectual property rights, and technology transfer frameworks, so that AI does not become a fresh driver of inequality.

These global concerns take on added importance against the backdrop of demographic changes, particularly in regions with ageing populations. As the working-age population share declines, many countries increasingly rely on technological progress to maintain productivity and support growing numbers of dependents. AI promises substantial benefits in automating complex tasks, optimising workflows, and generating new avenues for economic growth. Yet for AI to deliver these advantages without worsening inequality, national and international policies must be carefully calibrated to encourage inclusive growth, facilitate workforce transitions, and strengthen social infrastructures.

In sum, the transition from automation to AI highlights both continuities and divergences in the relationship between technology and employment. While the most pronounced effect of automation has been the erosion of middle-skill and routine roles, AI is now reaching into higher-skill, non-routine domains once perceived as safe from mechanisation. This transformation brings with it significant opportunities—including heightened innovation, productivity gains, and the potential enhancement of human creativity—while also presenting policymakers and societies with new challenges. Chief among these is ensuring that AI fosters inclusive human development, rather than exacerbating inequalities within and between nations at varying stages of digital infrastructure. In light of these considerations, strategies for investing in digital capacity, fortifying infrastructure, and prioritising AI-focused training must underpin any comprehensive policy framework. By acknowledging and proactively tackling these critical issues, governments, employers, and international institutions can help ensure that AI's transformative potential is harnessed for broad-based prosperity and equitable growth in the decades ahead.

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