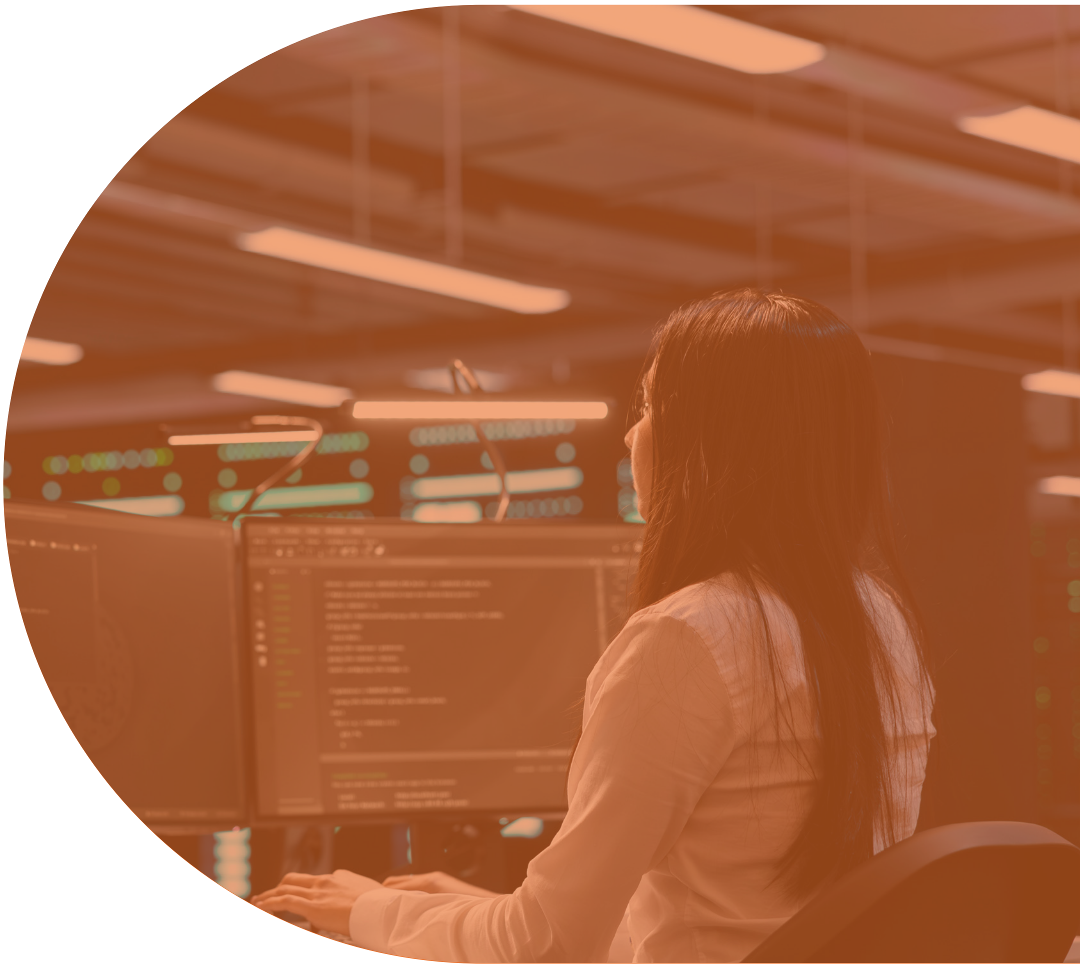
Generative Artificial Intelligence and Its Implications for Labor Markets in Developing Countries: A Review Essay



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Abstract

The unprecedented developments in artificial intelligence technology and its recent widespread availability hold transformative potential to reshape global economic dynamics and labor markets, though opinions on its effects vary greatly. Transformative or not, the irruption of AI has sparked ample public discussion as well as the rapid development of theoretical and empirical approaches to understand it. This review essay discusses recent perspectives, theories, and empirical evidence on the matter, and adds a perspective of the implications of this technology and of the policy discussion it has sparked, from the perspective of developing countries' economies. The latter is motivated by the relative scarcity of such perspectives in the current public debate, which seems to have minimized the potential effects on the interaction of labor markets between developing and developed countries, and on the potentially different within-country effects at different levels of development.

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I. Introduction

The unprecedented developments in artificial intelligence (AI) technology and its recent widespread availability hold transformative potential to reshape global economic dynamics, though opinions on its effects vary greatly (Acemoglu, 2024). Transformative or not, the irruption of AI has sparked ample public discussion as well as the rapid development of theoretical and empirical approaches to understand it. This review essay discusses recent perspectives, theories, and empirical evidence on the matter, and adds a perspective of the implications of this technology and of the policy discussion it has sparked, from the perspective of developing countries' economies. The latter is motivated by the relative scarcity of such perspectives in the current public debate, which seems to have minimized the potential effects on the interaction of labor markets between developing and developed countries, and on the potentially different within-country effects at different levels of development. The current view seems to be guided by the observation that previous episodes of information technology (IT)-induced technical change affected lower levels of the skills distribution, whereas "one of the things that sets AI apart is its ability to impact high-skilled jobs," which then imply greater risks and opportunities for advanced economies (Giorgieva, 2024). While the premise is certainly true, our analysis will attempt to shed light on the idea that such a transformative technology may have consequences well beyond the specific groups of high-skilled workers in developed countries.

While previous episodes of IT-induced technical change have been studied in depth (see Acemoglu & Restrepo, 2022 and the discussion in Appendix 2), there are four crucial differences between generative AI (GenAI) and the computing era we are leaving behind, as well as with earlier stages of GenAI adoption. These differences include 1) the fast adoption of these new technologies and their growth potential, 2) the democratization in the use of these technologies, 3) the capabilities or human skills that these new technologies can mimic, and 4) the reorganization of production between countries that these technologies may encompass. Besides the service sector, AI-based tools and systems can transform agriculture, health care, and education as well as make industries smarter and more effective. While it seems clear that the productivity gains at the aggregate level may be large, the full effects of these transformations for global labor markets are extremely difficult to foresee. Additionally, as argued above, a full picture of these effects must carefully consider outcomes in both developed and developing countries, as the latter have their own distinctive characteristics that may shape the ways in which AI impacts their population and labor market.

Two significant and related questions thus arise. First, how do these technologies affect labor division between countries? Changes in the supply, demand, and remuneration of skills in developed and developing economies must be determined jointly. However, a static view focuses primarily on high-skilled workers in wealthier countries who are currently at risk of displacement. In less developed economies, opportunities to take advantage of the potential benefits are less clear due to lower capital and skilled labor endowments, as well as weak institutions and regulations, though the widespread availability of a skills-enhancing technology may also be an opportunity for convergence. Relative prices of capital and labor also influence the potential opportunities and risks for developing countries. Moreover, the digital divide could exacerbate income inequality, with those having access to AI technologies becoming disproportionately wealthier and the access gap widening even further for developing countries. Developing countries may also lack comprehensive policy frameworks to manage AI's impact on labor, unlike developed nations with more robust regulatory structures. Last, if AI's global expansion leads to system concentration in developed countries and requires specifically trained but underpaid workers from developing countries, global inequality may increase. This could be a new form of production relocation, with productivity benefits predominantly accruing to developed economies.

Second, could GenAI potentially lead to universally positive or negative outcomes across skill tiers within countries? Alternatively, might the impacts be primarily concentrated among low- or high-skilled workers? Whereas automation has affected workers in the middle of the skills distribution (polarization hypothesis), generative GenAI has the potential to affect tasks and jobs associated with high-skilled workers, either by directly replacing them with technology or by enabling low-skilled workers to close the skill gap and compete with them, reducing existing inequalities. In this sense, GenAI may represent an opportunity for the comeback of middle-income/middle-skill workers, who were displaced by the technology-induced polarization of jobs. Alternatively, and probably depending on the type of tasks, GenAI may complement high-skilled workers and increase existing inequalities. However, it is important to consider whether these effects are the same for developed countries as for developing ones.

The speed and complexity of the changes involved in AI technology have prompted the development of an ambitious and lively research agenda addressing these questions. As expected, this agenda is primarily driven by the accumulation of knowledge in the academic hubs of developed countries, which often focus on issues specific to wealthy economies. While these contributions are undoubtedly welcome and valuable, as they contribute to genuine knowledge on the subject, the analysis of the AI revolution calls for a comprehensive framework that specifically addresses the consequences of AI emergence in developing countries.

This document aims to shed light on some of these issues by reviewing the available evidence and highlighting potential gaps. It is organized as follows. Section 2 systematizes the differences that exist between developing and developed countries that may shape the ways in which AI impacts its labor markets. Section 3 briefly explains how the new technologies work, their scope, and how they change the paradigm of the tasks and skills they can replace. Section 4 dives into how new technologies affect the division of labor and demand for workers between countries. Section 5 presents evidence on the impacts of new technologies on aggregate employment and among workers of different skill levels within countries. Finally, Section 6 concludes and suggests five major policy guidelines, including a research agenda, for developing countries.

II. The need for a developing country perspective

As stated in the introduction, the research agenda on AI mainly focuses on developed countries and on the specific issues arising in wealthy economies. Dismissing the impact on developed countries due to the concentration of GenAI's effects on the upper rung of the skills distribution—or extrapolating the conclusions and policy challenges emerging from studies of developed countries to developing ones—are probably not effective strategies. In this section, we discuss the specific characteristics that differentiate developing countries from their wealthier peers, and how these characteristics may shape the impact of new technology, presenting distinct challenges and opportunities.

Developing countries consist of distinct regions that differ in culture, history, institutions, and levels of development, which in turn affect areas like labor markets, infrastructure, and demographics. Broadly speaking, these subregions can be grouped into 1) South and Southeast Asia, 2) the Middle East and North Africa, 3) Latin America and the Caribbean (LAC), and 4) Sub-Saharan Africa. Despite their diversity, certain characteristics group and distinguish them from their wealthier peers: 1) larger levels of informality and inequality, 2) preexisting skills challenges, and 3) lower access to digital infrastructure. As will be discussed later in this section, these characteristics, among others, have resulted in these regions being systematic late adopters of new technologies throughout history.

2.1 Larger levels of informality and inequality

The informal economy is highly heterogeneous. In many settings, this is a result of low level of development, the inability of the economy to create formal quality jobs, and the inability of institutions to deliver and improve people's lives (OECD, 2023b). According to the OECD (2023b), informal employment represents 89% of total employment in low-income countries, 81.6% in lower-middle-income countries, 49.7% in upper-middle-income countries, and 15.9% in high-income countries. The percentage is highest in Africa (84.3%) but with significant differences between countries in the region. In Asia and Pacific, the rate of informal employment ranges from less than 20% in developed countries in the region, such as Australia or Japan, to almost 90% or more in Bangladesh, Cambodia, India, and Lao People's Democratic Republic. The Arab states have the third-highest regional level of informal employment (54%), while in the Americas, informal employment ranges from 9.8% in North America to 53.6% in LAC.

Informal workers in these regions are not only excluded from the protections afforded to formal workers but also lack access to basic public services, such as health care, education, and skills training (OECD, 2023b). Without the safety net of various developed welfare states, inequality in developing countries is a preexisting challenge. According to Albrieu (2022), while in the developed world digital transformation is fueling income inequality, developing countries' structural inequality is a key factor preventing structural transformation. Additionally, in environments with large sections of the workforce self-employed, working in family-based enterprises, or in the unregulated informal sector, skill development and usage differ significantly from those in formal sectors of developed countries (Brown, 2022). In this context, while in the developed world technological change affects secure and long-term jobs, in the less developed world these threats are compounded by the likely repercussions on the informal sector.

Firm informality is also high for some developing countries. For instance, according to Levy and Cruces (2021), over 80% of all firms in LAC are informal due to the large number of small firms. This has implications for productivity. According to the author, multicountry studies find large productivity differences between formal and informal firms, which mainly translate into productivity differences between small and large firms.

2.2 Preexisting skills challenges

According to Albrieu (2022), skilling and reskilling challenges are more complex for developing countries given that workers are excluded from formal education and training institutions due to lower coverage of secondary and tertiary education and the high prevalence of informality. Furthermore, those who attend these institutions suffer the consequences of lower-quality educational systems, implying that schooling is not the same as learning. This disparity in educational quality is quantified by Our World in Data, which portrays the learning-adjusted years of schooling (LAYS) for each country in 2020.[1] Developed by Filmer et al. (2018), this measure assesses the quality of education by considering the actual learning outcomes achieved by students in addition to the number of years of schooling completed. A higher LAYS value indicates that students have not only spent more time in school but have also achieved higher levels of learning outcomes. Conversely, a lower LAYS value suggests that students may have completed a certain number of years of schooling but have not acquired the expected level of knowledge and skills. As seen in the data, developed countries exhibit larger values of this

1 See https://ourworldindata.org/grapher/learning-adjusted-years-of-school-lays.

measure, while developing ones, mainly in Africa and the Middle East, exhibit lower values. In this context, the reform of study plans must be addressed, but new elements of analysis—low coverage, poor quality, scarce funding—also need to be considered for less developed countries.

These challenges translate into digital weaknesses. The available data are limited but suggest that digital literacy levels are relatively low in developing countries. According to an article published by Jann Lay and Katharina Fietz in Industrial Analytics Platform,[2] very few low-income countries report any data on the proportion of youth and adults with information and communication technology (ICT) skills. The data that are available point to huge discrepancies in digital skills across countries. In Chad and the Central African Republic, for example, only a very small fraction of adults (1.6% and 2.4%, respectively) has copied or moved a folder on a computer. The share of those who have used basic arithmetic formulas in a spreadsheet is also very low for most low- and middle-income countries. In poor African countries, including Chad, the Central African Republic, Niger, and Togo, fewer than 1.5% of individuals are equipped with these skills, compared with approximately 50% in highly skilled Korea. Cazzaniga et al. (2024) propose an AI Preparedness Index made up of a selected set of macro-structural indicators that are relevant for AI adoption.[3] According to the authors, low-income countries are underprepared across all dimensions to harness the benefits of AI, but weak digital infrastructure and a less digitally skilled labor force are a major concern. According to the World Bank (2021), more than half of the population in the developing world lacks basic digital skills, and the vast majority of those with digital skills lack more advanced skills in AI and machine learning.

Similarly, Butler et al. (2023) find that disparities in the adoption of new technologies follow the traditional digital divide. When examining searches on Bing for "ChatGPT" or "Chat GPT" and matching them with county-level demographic data, Daepp and Counts (2023) find that these searches are larger in countries with a higher share of college-educated individuals.

2 See https://iap.unido.org/articles/digital-skills-global-south-gaps-needs-and-progress#:~:text=The%20digital%20gap,-The%20levels%20of&text=The%20limited%20data%20available%20suggests,countries%20are%20also%20very%20considerable.

3 These are organized under four categories: (1) digital infrastructure, (2) innovation and economic integration, (3) human capital and labor market policies, and (4) regulation and ethics.

2.3 Lower access to digital infrastructure

Lower digital skills are influenced not only by challenges in education coverage and quality but also by access to digital infrastructure, a crucial determinant of ICT adoption. According to De Bastion and Mukku (2020), the digital divide mirrors the economic and social inequalities across the globe. They find that in low- and middle-income countries, just over 40% of the population was connected to the internet in 2020, compared to almost 75% in high-income countries. In LAC, the usage gap was 39% and 49% in Africa. They also find that average expenditure on mobile internet in developing countries was 3.8% of household income, whereas it was only 1.8% in the developed world. Moreover, the average cost for 1 gigabyte (GB) of data was 7.12% of the average monthly salary across Africa. In some countries, 1 GB cost as much as 20% of the average salary, which was unaffordable for large parts of the population. The fact that only 39% of the population in low-income countries had access to electricity in 2020 is another major constraint.

As highlighted by Gmyrek et al. (2024), software costs also likely impact the economic viability of adoption in developing countries. According to the authors, the basic licensing of products such as ChatGPT or Microsoft Copilot can cost around 20–30 USD per user per month, and costs of enterprise-level solutions, either based on simple API integration or more complex proprietary AI systems, can be significantly higher. In countries with high informality, such costs are prohibitive for many small enterprises.

All in all, largely due to these 3 characteristics, developing countries have not taken full advantage of global technological innovations in the past and remain a follower in the AI era. This means that even if we adopt an optimistic view of its impact at the global level, we cannot assume that exponential innovation and its consequences are a given for all countries. At the same time, this has implications for potentially increasing productivity and wealth gaps in the AI era. According to Chan et al. (2021), the players responsible for developing and implementing AI systems will be the ones to largely profit from the system. If these players are predominantly located in developed countries, a disproportionate share of economic benefit will accrue to these nations, exacerbating wealth inequality between countries. Additionally, Albrieu et al. (2018) note that the experience of previous industrial revolutions suggests that firms and countries that adopt new technologies the fastest are those that have the most growth opportunities. These episodes were marked by significant divergence in income, productivity, and well-being between countries, and GenAI might not be an exception.

III. The surge of generative AI and LLMs

Autor (2024) argues that AI, unlike the industrial and computer revolutions before it, marks an inflection point in the economic value of human expertise, signaling a transformative shift in the landscape of technological innovation. Complementing this view, Cazzaniga et al. (2024) provide a detailed description of the technologies involved: "AI represents a wide spectrum of technologies designed to enable machines to perceive, interpret, act, and learn with the intent to emulate human cognitive abilities. Across this spectrum, GenAI includes systems such as sophisticated large language models [LLMs] that can create new content, ranging from text to images, by learning from extensive training data. Other AI models, in contrast, are more specialized, focusing on discrete tasks such as pattern identification." Recently, LLMs have been developed and made available for mass use. These models—including the increasingly popular OpenAI's ChatGPT, Anthropic's Claude, and Google's Gemini—exhibit the ability to generate text and computer code of human-like quality, perform language translation, produce diverse creative content such as high-quality images from descriptive text, and provide informative responses to questions.

As stated in the introduction, there are at least four crucial differences between GenAI and the computing era we are leaving behind, as well as with earlier stages of AI: 1) the fast adoption of these new technologies and their growth potential, 2) the democratization in the use of these technologies, 3) the capabilities or the human skills these technologies can mimic, and 4) the reorganization of production between countries that these technologies may encompass.

Regarding the first aspect, within months of its public release in November 2022, ChatGPT became the fastest-growing consumer application in history (Choi and Schwarcz, 2023), with 100 million monthly active users around the globe (Stropoli, 2023) and about a third of employed Americans under 30 using it for work (Pew Research Center[4]). Additionally, earnings calls and social media (on X/Twitter) mentions of GenAI substantially increased following ChatGPT's release (Eisfeldt et al., 2023). This burgeoning interest has not only influenced public and corporate discourse but also significantly accelerated financial investments in the sector. Startup funding for AI, which increased from $500 million in 2010 to $4.2 billion by 2016, soared to $25 billion by the first half of 2023, representing 18% of global funding (Stropoli, 2023).

Regarding the second aspect, and partly related to the first, a substantial difference compared to the period just a couple of years ago is that we finally have the power of AI widely available. At an event on AI's impact on the African job market, hosted by X Space,[5] Phyllis Migwi noted that we have moved from an era where AI was accessible only by those with significant computing power in their data centers, capable of analyzing specially curated data sets, to a stage where GenAI uses all existing data on the internet and can interact with practically anyone who has access to a computer and the internet. Similarly, Matt Beane stated on his blog that "very few of us had the luck or the foresight to anticipate that we'd see the sudden arrival of a general-purpose technology that was available to billions of us for free—one that could perform a wide array of cognitive tasks very quickly and that interacted via an instantly familiar chat-based interface."[6] In this context, the ability to break down communication barriers between humans and machines reflects a major advancement. According to Briggs and Kodnani (2023), "just as the migration from command line programming (e.g., MS-DOS) to graphical user interfaces (e.g., Windows) enabled the development of programs (e.g., Office) that brought the power of the personal computer to the masses, the intuitive interfaces of the current generation of AI technologies could significantly increase their speed of adoption."

4 https://www.pewresearch.org/short-reads/2024/03/26/americans-use-of-chatgpt-is-ticking-up-but-few-trust-its-election-information/

5 For more information, see https://jacobsladder.africa/ai-impact-on-the-african-job-market-x-space/.

6 https://www.wildworldofwork.org/p/learning-and-development-the-new.

Third, as explained by Autor (2024), "pre-AI, computing's core capability was its faultless and nearly costless execution of routine, procedural tasks. Its Achilles' heel was its inability to master non-routine tasks requiring tacit knowledge. Artificial Intelligence's capabilities are precisely the inverse. In a case of cosmic irony, AI is not trustworthy with facts and numbers—it does not respect rules. AI is, however, remarkably effective at acquiring tacit knowledge. Rather than relying on hard-coded procedures, AI learns by example, gains mastery without explicit instruction and acquires capabilities that it was not explicitly engineered to possess." Following this perspective, the OECD (2023a) justifies publishing a new employment outlook edition due to the "astonishing progress that AI has made to a point that, in some areas, it has become difficult if not impossible to distinguish its output from that of humans." Similarly, Dell'Aqua et al. (2024) note that LLMS have capabilities that they were not specifically created to have and ones that are growing rapidly over time as model size and quality improve.

Nevertheless, these models also have their flaws. According to Dell'Aqua et al. (2024), LLMs often produce incorrect, but plausible, results (hallucinations or confabulations) and make other types of errors, including in math and when providing citations. According to the authors, the advantages of AI, while substantial, are similarly unclear to users. It performs well at some jobs and fails in other circumstances in ways that are difficult to predict in advance, at least for the average worker.

Finally, the expansion of GenAI can reshape offshoring and reshoring patterns. While it may be profitable for institutions that develop GenAI systems to establish extra-national data centers and laboratories, this expansion also affects what was recently seen as an opportunity for developing countries. For instance, the potential for offshored telemedicine may be substantially reduced by the adoption of GenAI in analysis medical imaging analysis. Moreover, the development of GenAI systems relies on large amounts of data, with data collection and labeling processes often being carried out in developing countries. Big tech companies have established research labs in these countries as AI becomes integrated into the livelihoods of consumers worldwide (Chan et al., 2021). These developments may be beneficial and imply global inclusion in AI, but they also carry risks, as further discussed in Section 4.

In this context, LLM-based chatbots are expected to significantly impact a wide range of jobs, from content creation, design, customer care, and marketing to the analysis of medical images. Thus, we must review and reconsider previous models to understand how they will impact labor markets within and between countries. The next two sections discuss these issues.

IV. The between-country effects of GenAI

In a globalized world, it is crucial to understand how AI affects preexisting disparities and labor localization patterns between countries. This section analyzes how AI affects the division of labor and demand for workers between countries, as well as possible implications for preexisting productivity gaps between developed and developing countries.

The scope of what AI can do has the potential to reshape offshoring and reshoring patterns while creating new ones. First, if AI leads to the replacement of tasks currently performed overseas, it could potentially reduce incentives for offshoring. This scenario assumes that AI improves domestic labor conditions enough to negate the advantages of outsourcing to lower-cost regions. Consequently, AI could indirectly limit offshoring by making domestic labor more competitive. There have been some cases of impact already. For instance, "Foxconn replac[ed] 30 percent of its workforce when it introduced robots, and 1,000 lost jobs in Vietnam when Adidas shuttered a factory and moved production to "speed factories" in Germany and the US."7

Efforts have been made to capture the effects of automation technologies on offshoring. Specifically, Carbonero et al. (2020) assess the cross-country effects of robots, finding that in developed countries, they reduced offshoring and had a negative impact on employment in emerging economies of 8% over 2005–2014. The authors review similar research (Faber, 2018; Artuc et al., 2019) that find negative impacts of robot exposure for the specific case of Mexican employment and US imports from Mexico. Alonso et al. (2020) consider a model with two types of labor, with "robots" substituting for one type ("unskilled") and complementing the other

7 See https://www.cgdev.org/publication/automation-and-ai-implications-african-development-prospects?deliveryName=DM214429.

("skilled"). They find a permanent decline in the terms of trade in the developing region, insofar as it is relatively rich in unskilled labor. With this additional channel, the developing country could observe a fall in both relative and absolute GDP.

As noted by Carbonero et al. (2020), robotization provides a good proxy for the impact of automation on mechanical tasks; however, these tasks represent only a subset of a broader range of automation. Collecting data on AI would allow researchers to widen the analysis. For example, Ernst et al. (2018) find that the possibility of using cloud-based solutions has reduced the advantage of having low-cost programmers in developing countries. They cite projections of job losses in India, Philippines, Poland, and the United States with different automation paces, suggesting that countries that previously benefited from offshoring business processes stand to suffer more job losses.

Similarly, a series of services exports and offshoring that have flourished in developing countries (e.g., call centers, telemedicine) may be severely affected by the substitution effects of AI technology and the resulting fall in prices. The business process outsourcing (BPO) sector, which first emerged in the US and Europe in the 1990s and expanded in the 2000s, was enabled by growth in ICT and the spread of the internet. This allowed new employment opportunities to reach poorer segments of the world's labor markets and enabled new businesses to leverage their competitive advantage by accessing cheap labor and a knowledge base in ICT (Muldoon et al., 2023). Studies analyzing the incipient effects of AI on these dynamics are practically inexistent and crucial for policymakers to prepare for possible reductions in labor demand.

Second, AI could exacerbate existing disparities in offshoring patterns or create new forms of inequality. For example, as machine learning algorithms become more sophisticated and scale up, AI companies increasingly need high-quality and low-cost data sources (Muldoon et al., 2024). Cognilytica (2019) estimates that that data preparation tasks such as collection, cleaning, and labeling comprise over 80% of the machine learning development process. The back end of AI-based tools and systems is powered not only by qualified machine learning engineers but also by a large, often invisible workforce engaged in "data work,"8 including annotating, verifying, and labeling data. The market for these services is estimated to be worth between US $1 and $3 billion and is expected to see double-digit growth over the next five years (United Nations [UN] & International Labour Organization [ILO], 2024). Although precise figures for the number of people working as data labelers are unavailable, estimates suggest tens of millions are employed in this capacity. Additionally, while demand is largely concentrated in developed countries, the supply comes from developing ones.

Schematically, the global demand and supply dynamics of this data work are embedded in two large business models: BPOs and digital platforms. As previously mentioned, BPOs can be traditional, usually located in developing countries such as the Philippines, India, Kenya, and Venezuela, or they can have greater levels of specialization in AI systems. The latter has routinely become a destination for outsourced data labeling labor, with companies such as Scale AI and Mighty AI relying on workers in developing countries (Okolo, 2023; Chan et al., 2021). Companies have begun to proliferate in the region as well (e.g., Sama in East Africa, Cloudfactory in Nepal, Fastagger in Kenya, Sebenz.ai in South Africa, and Supahands in Malaysia). Compared to digital platforms, BPOs can be more specialized and focus on specific types of data services and particular domains of application, such as autonomous vehicles or computer vision (Muldoon et al., 2024). They also tend to be more expensive as they can guarantee a higher quality of service with direct lines of communication between the client, management, and workers.

As warned by Chan et al. (2021), as AI development continues to scale, the expansion of these companies opens the door for low-skilled laborers to enter the workforce but also presents a risk of exploitation. For example, Muldoon et al. (2023) conducted fieldwork at Sama, one of the largest BPOs in East Africa, and found "alarming accounts of low wages, insecure work, a tightly disciplined labour management process, gender-based exploitation and harassment and a system designed to extract value from low-paid workers to produce profits for investors."

8 Muldoon et al. (2024) use the term "data work" to describe the activity of curating, annotating, and verifying datasets. The authors note that "AI data workers' labour is embedded not only in larger production networks of AI systems, but also in 'planetary labour markets' in which tech companies are searching for the cheapest possible source of labour to fulfil their AI data work needs (Posada, 2021). As a result, much of this work occurs in different locations in developing countries, including Latin America, Asia, Africa, and the Middle East (Jones, 2021b; Muldoon et al., 2023; Posada, 2021)."

According to the authors, competitive market-based dynamics generate a powerful force that pushes such companies toward limiting the actual social impact of their business model in favor of ensuring higher profit margins. At the same time, recent coverage has shed light on the harms these workers have faced in East Africa when exposed to graphic content.9 Nevertheless, they do not discount the genuine benefits that workers receive from having access to employment opportunities,10 as the welfare levels in a counterfactual situation without these jobs are unclear. In any case, the clear message is that policymakers need to devise ways for a better integration into the GenAI global value chain.

Digital platforms, or generalist microwork platforms, as labeled by Muldoon et al. (2024), operate online marketplaces for digital tasks that allow requesters to post a variety of jobs online to be performed remotely. One example is Amazon Mechanical Turk (MTurk), which allows the real-time hiring of labor for a myriad of tasks, from IT programming to graphic design to routine clerical tasks (Berg et al., 2019). According to Muldoon et al. (2024), the ease, flexibility, and low cost of outsourcing work on digital labor platforms has resulted in their growth, which will likely continue into the future. The authors also note that, as in the case of BPOs, the growth of the AI data work sector has led to the emergence of new competitors to traditional platforms like MTurk that offer more specialized services to support AI systems. Additionally, emerging AI data companies such as Mighty AI, Hive AI, and Playment, with growing client bases, are often preferred by clients who value the speed and low cost of traditional crowdsourcing platforms but need higher precision for their AI models, as small errors in training data can reduce effectiveness.

While working on digital platforms provides workers with flexibility, allowing those with disabilities, caring responsibilities, or those in rural or economically depressed areas to earn an income, their working conditions raise some concerns. These platforms, like most other types of

9 See, for instance, https://time.com/6247678/openai-chatgpt-kenya-workers/.

10 They noted the following: "Many workers we interviewed were thankful for their jobs and saw them as a lifeline in an otherwise difficult job market. It provided them with a source of relatively stable income which they used to support themselves and their families. Employment with Sama had been life changing for those fortunate enough to stay at the company for a number of years. Some of these workers had through strict discipline managed to accrue savings and invest in assets and their future education. In the absence of Sama hiring marginalised individuals, some of its employees would experience challenges finding similar work. In one sense, since its founding in 2008, Sama has had a demonstrable impact on the 15,083 individuals employed by the organisation and their 41,157 dependents, which should not be overlooked."

digital labor platforms, often label their workers as independent contractors or self-employed, resulting in a lack of labor protection and employment-provided social security benefits. In this context, research has found a high proportion of workers to be earning below the prevailing minimum wage in their region. These low earnings were also partly due to their inability to obtain tasks on a continuous basis and the unpaid time that they spent identifying suitable tasks (Berg et al., 2019; Chan et al. 2021). Power dynamics on these platforms also present issues, as clients hold all the power (Chan et al., 2021). For instance, on many platforms, clients can reject work and refuse payment with little or no justification, while keeping and retaining the benefit of the completed work (Berg et al., 2019).

While these challenges affect workers around the world, they may become exacerbated in developing countries. If AI's global expansion results in its systems being concentrated in developed countries and demanding specifically trained workers (even if not necessarily qualified) with excessive workloads and lower salaries than those paid in developed countries, global inequality may increase. This would be a new form of production relocation, the benefits of which in terms of productivity gains would be concentrated in developed economies.

Nevertheless, there is a positive side. AI has the potential to increase productivity in underdeveloped regions by facilitating access to education, health care, credit, better agricultural management, and more efficient governments. In this context, new technologies can equip workers with tools to navigate this new era in a more advantageous and competitive position than in previous episodes of IT-driven technical change (see Appendix 1).

V. Models and evidence on AI's within-country effects

Studies addressing how AI can impact labor demand stem from two approaches. The first approach is the "traditional" or technical change model, which views technology as a substitute for individual worker tasks and studies how workers and tasks can complement or substitute for technology. These models, and their recent extensions to incorporate GenAI, tend to be more pessimistic about the promise of AI in reducing inequality. The second approach is more recent and analyzes possible impacts on the productivity of workers with different ability or skill levels. Studies using this approach usually employ experimental evidence and tend to find more optimistic results regarding inequality and the overall employment effects of GenAI. We refer to these series of models as the "experimental evidence" literature.

5.1 Technical change models

A vast strand of literature has studied the effects of labor-substituting automation technologies pre-AI (see Appendix 2 and Restrepo, 2023 for more details). Building on this, the task-based approach has emerged as the preferred model in economics to study current automation processes, including the digitalization and robotization of certain tasks. Conceptually, "the task model postulates that producing goods and services requires the completion of tasks that can be assigned to groups of workers, defined by their skills and abilities, or robots and machines. The crucial takeaway of this framework is that the relative labor demand for groups of workers whose tasks are taken over by robots falls with automation, and the level of labor demand for these groups might even fall depending on the productivity gains that come with robot adoption, and workers' ability to transition to occupations unaffected by task displacement" (Comunale & Manera, 2024). In this context, these models suggest that technological advancements, particularly in automation and computerization, have contributed to job polarization. This means that employment growth occurred primarily in high-skilled, high-wage occupations and low-skilled, low-wage occupations, while employment in middle-skilled, middle-wage occupations declined. Numerous studies have shown the relationship between automation technologies and wage inequality in the US, steered by relative wage declines for workers specializing in routine tasks (Autor et al., 2006; Van Reenen, 2011; Acemoglu & Restrepo, 2022). However, the picture looks different for developing countries. For instance, over the last two decades, wage inequality fell across LAC (Gasparini, 2019).

Even though the same framework can be used for AI instead of robots, potential task exposure to AI appears to be different. Eloundou et al. (2023), among the most cited authors in the literature using the traditional model framework, update it by incorporating new technologies such as GenAI. Specifically, the authors analyze O*NET tasks exposed to LLMs and then aggregate them by occupation and industry in the US.[11] According to the authors, "approximately 80% of the U.S. workforce could have at least 10% of their work tasks affected by the introduction of GPTs, while around 19% of workers may see at least 50% of their tasks impacted." Their paper builds on the work of Brynjolfsson et al. (2018, 2023a), who devise a new rubric to assess worker activities for their suitability for machine learning. Briggs and Kodnani (2023) use the O*NET database on the task context of over 900 occupations in the US and extend it to the European ESCO database to estimate the share of total work exposed to labor-saving automation by AI by occupation and industry. Webb (2019) uses the overlap between the text of job task descriptions and the text of AI patents to construct a measure of the exposure of tasks to automation.

Similar works are reviewed by Cazzaniga et al. (2024). In their review, they note that Felten et al. (2021) define "exposure" (which may involve substitution or augmentation) to AI as the degree of overlap between AI applications and required human abilities in each occupation. To understand each occupation's level of complementarity and exposure to AI, the authors build an index (also based on O*NET categorizations) and adapt it to account for the recent advancement of LLMs. Alternatively, Pizzinelli et al. (2023) examine the skills and work contexts of each occupation and build an index considering exposure to AI but also complementarity. The work of Cazzaniga et al. (2024) is based on the latter and allows for comparison between countries with different income levels and provides a detailed analysis for four developing countries (Brazil, Colombia, South Africa, and India). Carbonero et al. (2023) develop a methodology that allows for translating existing scores of AI impacts to contexts of other countries at the level of work activities. Gmyrek et al. (2023) use the GPT-4 model to estimate task-level scores of potential exposures and then estimate potential employment effects at the global level as well as by country income group. Last, Benitez and Parrado (2024) conduct a related exercise, developing an AI-created index of occupational exposure to AI, and apply it to data from Mexico and the United States.

[11] Chen et al. (2023) use the same framework and apply it to the Chinese labor market.

On the aggregate level, the work by Cazzaniga et al. (2024) suggests that almost 40% of global employment is exposed to AI. In advanced economies, this figure rises to about 60% of jobs[12]. According to Cazzaniga et al. (2024), roughly half of the exposed jobs may benefit from AI integration, enhancing productivity. For the other half, AI applications may execute tasks currently performed by humans, which could lower labor demand, resulting in lower wages and reduced hiring. In the most extreme cases, some of these jobs may disappear entirely. The authors also find that in emerging markets and low-income economies, AI exposure is expected to be 40% and 26%, respectively. This result is similar to those of Gmyrek et al. (2023) and Weller (2020, discussed in Appendix 2), who note that the lower risk of job loss in less developed countries stems from difficulties in adopting new technologies, which in turn hampers productivity growth.

Regarding different types of skills, Elondou et al. (2023) find that the importance of science and critical thinking skills is strongly and negatively associated with exposure, suggesting that occupations requiring these skills are less likely to be impacted by current LLMs. Conversely, and in contrast to the previous technological wave, programming and writing skills show a strong positive association with exposure, implying that occupations involving these skills are more susceptible to being influenced by LLMs. This should not come as a surprise, as these skills align closely with the tasks that AI tools are more specialized in. This idea, particularly its short-term validation, is examined by Demirci et al. (2023), who study the impact of GenAI on the demand for online freelancers using a large dataset from a leading global freelancing platform. They find that writing was the job category most affected by ChatGPT, followed by software, app and web development, and engineering. More specifically, they find a 21% decrease in the number of job posts for automation-prone jobs related to writing and coding—compared to jobs requiring manual-intensive skills, within eight months after Chat GPT's introduction—and a 17% decrease in the number of job posts related to image creation following the introduction of image-generating AI technologies. Using Google Trends, the authors also find that the more pronounced decline in the demand for freelancers within automation-prone jobs correlates with

12 Briggs and Kodnani (2023) find similar results for the US and Europe

higher public awareness of ChatGPT's substitutability.

Similarly, returning to the task-based frameworks discussed in this section, Webb (2019) finds that in contrast to software and robots, AI is directed at high-skilled tasks. Assuming that the historical pattern of long-run substitution continues, the author estimates that AI will reduce 90:10 wage inequality. Additionally, Felten et al. (2023) find that occupations with higher wages are more likely to be exposed to rapid advances in LLMs from products such as ChatGPT. However, as warned by Korinek and Suh (2024), ongoing advances in robotics make it likely that even nonroutine manual jobs will be affected by the recent wave of progress in foundation models. In a different type of exercise, returning to the aggregate distinction between low- and high-skilled workers used in the pioneering works, Bloom et al. (2024) propose a production function that includes traditional physical capital in the form of assembly lines and machines; industrial robots that are a comparatively good substitute for low-skilled workers; and AI, which is a comparatively good substitute for high-skilled workers and simulates the effects of a contemporaneous rise in the stock of industrial robots and in the stock of AI on the skill premium, using data for the US.13 According to the authors, as long as substitution between AI and high-skilled workers is easier than between low- and high-skilled workers, the deployment of AI will have stronger effects on the wages of high-skilled workers. Thus, increasing the use of AI reduces the skill premium.

Nevertheless, not only exposure, but also complementarity must be considered. Cazzaniga et al. (2024) find a high complementarity between new technologies and high-skilled workers, and higher potential gains positively correlated with income, which may lead to higher labor income inequality. These findings apply to both developing and developed countries. Regarding qualifications, the authors find that "in all countries examined, higher education levels are associated with a greater share of employment in high-exposure occupations, but this is especially pronounced in occupations with high complementarity." Even though higher levels of exposure support the popular view that AI could more strongly affect high-skilled workers, higher

[13] According to the authors, high-skill workers are those with a bachelor's degree or higher, while low-skill workers do not have a university degree.

exposure is alleviated by greater potential for complementarity.

Similarly, income dynamics mirror these patterns. Cazzaniga et al. (2024) further find that "consistent with popular discourse, AI differs from traditional automation by potentially affecting jobs of workers throughout the income distribution. However, employment in occupations that have a high potential for complementarity with AI is more concentrated in the upper-income quantiles. The correlation between earnings and potential complementarity is consistent with the findings on education level and is even more pronounced for emerging market economies." According to the authors, college-educated workers are better prepared to move from jobs at risk of displacement to high-complementarity jobs. For example, they note that "in the UK and Brazil … college-educated individuals historically moved more easily from jobs now assessed to have high displacement potential to those with high complementarity. In contrast, workers without postsecondary education show reduced mobility."

Regarding complementarity and its comparison across countries, the UN and ILO (2024) find a significantly larger share of total employment in occupations with high augmentation potential, which holds across regions. In this context, the potential for occupations to benefit from the productivity-enhancing effects of the technology should be relatively similar across countries. Nevertheless, when including restrictions on the adoption of new technologies, such as those faced by developing economies, the situation changes. Gymrek et al. (2024) provide a first attempt at adapting measures of job exposure to GenAI in the context of developing countries, where even workers in occupations that are generally expected to benefit from GenAI may not be able to reap its benefits due to poor access to digital infrastructure. According to the authors, between 30% and 40% of employment in LAC is exposed in some way to GenAI (either to automation, augmentation, or what they call "the big unknown," occupations, which, depending on the progress of technology and the use of adjacent technological applications, could fall closer to automation or augmentation). The share of jobs that could benefit from productive transformation with GenAI is consistently higher than those with automation risks across all LAC countries, ranging between 8% and 12% of employment across countries. Nevertheless, half of these positions' augmentation are hampered by digital shortcomings that will prevent them from realizing this transformation. At the same time, to better understand how the first-order effects of GenAI may affect inequality, the authors provide a detailed profile of the socioeconomic groups most exposed to this technology. They find that the middle class's jobs and earnings have the highest overall exposure to GenAI, with many possible directions that this transformation can take.14

Finally, using this framework, the literature shows that women work in occupations and perform tasks that tend to be more exposed to the impacts of AI. However, other factors influence the final effect of AI on women's jobs (see Appendix 3 for more details).

All in all, although these models effectively describe the main stylized facts, some caveats must be mentioned. First, there are bottlenecks for some new technologies, varying at the individual, company, and even sector level (Carter and Hersh, 2022; Cazzaniga et al., 2024). As noted by Enlondou et al. (2023), "although the potential for tasks to be affected is vast, LLMs and LLM-powered software must be incorporated into broader systems to fully realize this potential. As is common with general-purpose technologies, co-invention barriers may initially impede the rapid diffusion of GPTs into economic applications."

One of these barriers is the level of confidence humans place on these tools. For instance, even though judges are highly exposed to LLMs, they are also highly protected from displacement because society is currently unlikely to delegate judicial rulings to unsupervised AI (Cazzaniga et al., 2024; Elondou et al., 2023). As reviewed by Carter and Hersh (2022), workers' resistance to AI augmentation can be understood from several perspectives, including a status quo bias (Kim and Kankanhalli, 2009), fear of job substitution or loss of power (Acemoglu, 2022), and an overall distrust of algorithms generally referred to as "algorithm aversion" (Burton et al.,

[14] According to the authors, "given that educational attainment and earnings gaps across skills groups have been important drivers of income inequality in LAC (Azevedo et al. 2013), the impact of GenAI that follows the existing labor market structures would likely also have an effect on the overall income inequality. In the best-case scenario, GenAI would boost the productivity of lower-skilled workers in the exposed occupations, allowing them to access higher incomes and therefore leading to a more broad-based income distribution. In the worst-case scenario, the technological transition could result in the automation of largely female-held jobs in the clerical, technical and professional occupations, while the opportunities for new GenAI-augmented jobs could be limited, given the high concentration of current employment in elementary occupations and in the informal sector, where technology adoption and private sector investment are low."

2020). Social preferences and available alternatives also play a role. For example, in low-income countries, where there are relatively fewer trained doctors, scalable AI-backed medical consultations may be viewed as an attractive option (Cazzaniga et al., 2024). In this context, as summarized by Elondou et al. (2023), "the adoption of LLMs will vary across different economic sectors due to factors such as data availability, regulatory environment, and the distribution of power and interests," and social preferences—and the models analyzed in this section—may not be able to incorporate all these possibilities. Other barriers are related to infrastructure; according to Goldman Sachs (2024), the current chips shortage and looming power shortages will constrain AI growth and adoption.

Acemoglu (2024) also provides an important contribution to this discussion. Contrary to most of the studies predicting very large and disruptive effects of GenAI for the world economy, the author documents only modest effects on total factor productivity over the medium term (10 years). Regarding its impact on inequality, he highlights that since AI has the potential to increase the productivity of low-skill workers, at least in certain tasks, "this may increase rather than reduce inequality," and that recent developments in GenAI may in fact increase inequality less than previous technical change such as automation "because their impact is more equally distributed across demographic groups." Importantly, he also highlights the prediction that GenAI will increase inequality between capital and labor income.

Finally, in another seminal contribution, Korinek and Suh (2024) expand the scope of previous models by introducing artificial general intelligence, defined as the ability of AI systems to perform all tasks that humans can perform. Conceptually, the authors examine the limit case of what happens if either all work tasks are automated or if we asymptote toward a world in which all tasks are automated. To do so, they introduce two novel and crucial elements into their model: the decomposition of human work into atomistic tasks that differ in their level of complexity and the measure of task complexity given by the amount of compute (shorthand for computational resources) required for the execution of a task by machines. This novel approach opens up a new perspective for analyzing the economic impact of AI.

The authors find that if the task distribution has an infinite Pareto tail, reflecting unlimited complexity of human work, then wages can rise indefinitely if the tail is sufficiently thick, as capital accumulation automates ever more complex tasks but there always remains enough for human labor. However, if the Pareto tail is too thin, then automation ultimately outpaces capital accumulation and causes a collapse in wages. In this context, there may be an ever-growing inequality among workers: a shrinking fraction of workers at the top may see their incomes rise without bounds, whereas a fraction of the population that asymptotes toward one will see wages collapse to levels equivalent to the return on capital. At the same time, using the economy's factor price frontier, the authors show that the effects of automation follow an inverse U-shape, first increasing wages by using abundant capital and then eventually decreasing them due to labor displacement. They also find that sufficient capital accumulation is essential to prevent automation from depressing wages.

The atomistic task assumption is particularly interesting since it challenges some observations provided by the traditional literature. First, these atomistic tasks are significantly smaller than those listed in O*NET.15 According to the authors, the "recent literature on technology on labor markets observes that innovation typically gives rise to new job tasks (e.g., Acemoglu & Restrepo, 2018; Autor, 2019). This holds true when viewed from the perspective of high-level job tasks such as those captured by O*Net. However, when viewed from an atomistic level that reflects basic brain functions, innovation merely recombines atomistic tasks in novel ways to produce novel high-level tasks and jobs." This insight relates to one of the limitations that Elondou et al. (2023) observe in traditional models: the potential discrepancies between theoretical and practical performance, particularly in complex, open-ended, and domain-specific tasks. Experimental evidence models attempt to shed light on some of these issues, highlighting that within the same occupation or task, workers often differ in seniority, experience, abilities, or skills. Consequently, automation might affect them differently even when they perform the same

15 To understand this concept, the authors offer the example of the "the top-5 O*Net tasks of economists: to study data; conduct and disseminate research; compile, analyze and report data; supervise research; and teach. Each of these O*Net job tasks involves a wide variety of different atomistic tasks. For example, the O*Net task teach theories of economics may require first planning the overall task, recalling different economic theories, synthesizing a structure, preparing slides, formulating lectures, synthesizing speech and affect, decoding and responding to student questions, preparing problem sets, distributing problem sets, grading problem sets, and so on all while keeping track of the plan. It may also require tasks such as recognizing emotional expressions on students' faces, using theory of mind to evaluate student progress and dynamically adjust the structure, etc. All of these tasks involve a set of basic human brain functions, which constitute a form of computation."

task.

Finally, regarding our review's focus on developing countries, it is worth mentioning that although these traditional models can be adapted to capture the different realities of these countries (regarding barriers to technology adoption), they still cannot predict how results might change if we allowed these analyses to model worker mobility in a digital and globalized world, along with the offshoring trends described in Section 4.

5.2 New experimental evidence on GenAI's impact

Research based on experimental evidence shifts away from more abstract discussions and stylized facts to study the impact of GenAI on very concrete and specific tasks. Their outcomes tend to be more optimistic: LLM-based chatbots may have an "equalizing effect," whereby less advantaged workers benefit the most from their adoption, while their impact on the rest is more limited. However, there are some nuances to consider.

In theory, and according to Agrawal et al. (2023), task automation driven by advances in AI can improve the value of the skills of many workers, expand the pool of available workers to perform other tasks, and, in the process, increase labor income and potentially reduce inequality. The authors call this phenomenon the "Turing Transformation," noting that "the distributional effects of technology depend more on which workers have tasks that get automated than on the fact of automation per se."

Agrawal et al. (2023) cite some examples of how some new automation technologies might reduce entry barriers in some occupations, allowing less qualified workers to perform. For instance, they note that automating the taxi driver's competitive advantage (memory skills and the discipline to study maps16) has created opportunity for millions: "By combining navigation tools with digital taxi dispatch, Uber and Lyft have enabled almost anyone with a car to provide

16 The authors use the example of London, where taxi drivers had to pass a complex exam to prove "The Knowledge" of the maps and the complicated road networks in the city.

the same service as taxi drivers." Another interesting example is in the health sector.[17] Since diagnosis is a key human skill in medicine, AI-assisted diagnosis can boost the career and possibly wages of less qualified medical professionals (registered nurses, pharmacists, physician assistants, or paramedics), to the detriment of doctors. To cite one more example, people who speak multiple languages have an advantage in many international business opportunities. While AI can be bad news for translators,[18] it is likely good news for many others. Agrawal et al. (2023) note that "Brynjolfsson et al. (2019) report that AIs used for translation enhance the capacity of sellers on eBay, increasing exports by 17.5%. AI that automates language translation enables enhanced communication across the world. It likely means more trade, more travel, faster integration into workplaces for recent immigrants, more cross-cultural exchange of ideas, and perhaps even different social networks." The same might apply to writing skills. In this context, automation technologies that replicate the tasks of some human workers can enhance opportunities for others, and the examples provided by the authors typically benefit those with lower socioeconomic status, often at the expense of more highly paid individuals.

As previously mentioned, new efforts in the economic literature focus on the potential equalizing effect of GenAI, examining very specific tasks. For instance, Noy and Zhang (2023) run a lab experiment in which 453 college-educated professionals are recruited to complete incentivized writing tasks ("mid-level professional tasks"), using or not using ChatGPT. They find that inequality between workers decreased, with low-ability workers benefiting the most from ChatGPT. The authors also analyze the heterogeneous effects of ChatGPT across ability levels by associating ability with the score obtained in a pre-experiment task, similar to the one carried out during the experiment. The distinction in ability level is established by evaluating the quality of an initial writing task.

Similarly, Choi and Schwarcz (2023) administer law school exams to students with and

17 A growing strand of literature shows the promising results of AI in different fields of medicine, such as medical imaging and the generation of discharge summaries and patient clinical letters. For instance, Eriksen et al. (2023) assess the performance of the newly released GPT-4 in diagnosing complex medical case challenges. The authors compare the success rate to that of medical journal readers, finding that GPT-4 correctly diagnosed 57% of cases, outperforming 99.98% of simulated human readers generated from online answers.

18 Yilmaz et al. (2023) use Google's introduction of neural network-based translation (GNNT) in 2016–2017 as a natural experiment to examine the substitution of human translators by AI in the context of a large online labor market. They find that it reduces the number of (human translation) transactions at both the overall market and individual translator levels. They also find a stronger effect on translation tasks with analytical elements, as compared to those with cultural and emotional elements.

without access to a GPT-4 based chat. They find that assistance from GPT-4 significantly enhanced performance on simple multiple-choice questions but not on complex essay questions. Additionally, students at the bottom of the class saw significant performance gains with AI assistance, while those at the top experienced declines.

Brynjolfsson et al. (2023b) study the staggered introduction of a GenAI-based conversational assistant using data from 5,179 customer support agents in a real-world job setting. The authors find that access to the tool increased productivity, as measured by the number of chats handled per hour and a reduction in the time per chat (though with a smaller effect for the main outcome, issues resolved per hour), with the greatest impact on novice and low-skilled workers and a minimal impact on experienced and highly skilled workers. The authors posit that the AI tool allowed less able workers to acquire some of the knowledge of their more skilled peers (on whose past output the AI tool was trained), and also helped less experienced workers quickly improve in their jobs. Unlike the previous examples, the setting of this seminal study was a real-world Fortune 500 company, so the tasks are realistic by definition.

All these examples use a relatively homogeneous sample of subjects regarding skills or educational attainment. In Noy and Zhang (2023), all participants were college graduates, meaning they are usually classified in the literature as high skilled. Similarly, Choi and Schwarcz (2023) use Yale law students. Finally, Brynjolfsson et al. (2023b) study workers from a single firm at the same position, where it is likely that the firm recruited workers with similar qualifications. However, these papers do not directly address the effect of GenAI on inequality between high- and low-skilled workers.

In a controlled experiment, Peng et al. (2023) show that GitHub Copilot, a GenAI-based programming aid, significantly increased programmer productivity19 and was more helpful to developers with less experience. According to the authors, "developers with less programming experience, older programmers, and those who program more hours per day benefited the most." Unlike the previous papers mentioned, this work uses a more heterogeneous group,

19 Similarly, a GitHub survey of more than 2,000 developers on the use of Copilot showed that "88% of surveyed respondents commented feeling more productive, 74% reported being able to focus on more satisfying work, and 88% claimed to have completed tasks more quickly" (Maslej et al., 2023).

including participants both with and without college degrees (though this last variable was not found significant). Also in the area of programming but for students, Nie et al. (2024) conduct a large-scale randomized control trial (RCT) with 5,831 students from 146 countries in an online coding class in which some students are provided with access to a chat interface with GPT-4. They find positive benefits on exam performance for adopters, but for all students, the advertisement of GPT-4 leads to a significant average decrease in exam participation and course engagement. However, this decrease is modulated by the student's country of origin. They also find that offering access to LLMs to students from low human development index countries increases their exam participation rate, on average.

In Doshi and Hauser (2023)'s two-phase experimental online study, the authors find that access to GenAI enhances creativity, with less creative writers experiencing greater uplifts for their stories. The authors recruited 500 participants to participate in the experiment from the Prolific platform, and writers were not selected based on prior writing skills or their creativity.

Recent work by Haslberger et al. (2023) highlights some nuance in these trends. The authors conduct a pre-registered online experiment with a representative sample of the UK working-age population and randomly assign participants to treatments that encourage or discourage the use of ChatGPT. They then ask them to complete a set of tasks with varying complexity and ambiguity. Their results show "that exposure to ChatGPT increased productivity in all tasks, with greater benefits observed in more complex and less ambiguous tasks. ChatGPT did reduce performance inequality within occupational groups in most cases, but not between educational or occupational groups. Inequalities between younger and older workers even increased. This study indicates that generative AI has the potential to improve worker performance in a wide array of tasks, but the impact on aggregate inequalities is likely to depend on task-specific features and workers' characteristics."

Similarly, Jia et al. (2024) conduct a field experiment at a telemarketing company to examine AI assistance in the form of a sequential division of labor within organizations: in a task, AI handles the initial portion, which is well-codified and repetitive, and employees focus on the subsequent portion, involving higher-level problem-solving. The results show that enhanced creativity—which, according to the authors, leads to increased productivity—is much more pronounced for higher-skilled employees.[20] Likewise, Roldan-Mones (2024) runs an RCT with undergraduate students in a debating competition, where participants are randomly assigned to either GenAI support for debate preparation or conventional internet resources. The author finds that high-performing students and those with a stronger academic background benefit significantly more from GenAI than their lower-performing counterparts.[21] According to the author, "when tasks require higher-order skills, and answers cannot be directly extracted from the AI and copy pasted, high-skilled workers are likely to benefit more of the advantages of GenAI." Similarly, Kim and Moon (2024) run a controlled laboratory experiment to examine whether ChatGPT's aid could increase participants' performance in reading and writing, mathematical problem-solving, and computational thinking. The authors find that math scores significantly decreased with ChatGPT's assistance because the low-ability subjects could not discern the hallucinated answers with the correct ones.

Relatedly, another nuance to consider is that GenAI models can produce incorrect, but plausible, results (hallucinations or confabulations), and the value and downsides of AI may be difficult for workers and organizations to grasp. To study this, Dell'Aqua et al. (2024) conduct an experiment with Boston Consulting Group, a global management consulting firm, to examine the performance implications of AI on realistic, complex, and knowledge-intensive tasks. After establishing a performance baseline on a similar task, subjects were randomly assigned to one of three conditions: no AI access, GPT-4 AI access, or GPT-4 AI access with a prompt engineering overview. The authors find that the capabilities of AI create a "jagged technological frontier," where some tasks are easily done by AI, while others, though seemingly similar in difficulty level, are outside its current capability. For tasks within the frontier of AI capabilities, consultants using AI were significantly more productive (completed 12.2% more tasks, on average, and completed tasks 25.1% more quickly) and produced significantly higher-quality results.

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20 The authors define skills as the domain expertise in carrying out tasks required by their jobs. Specifically, they rank employees based on their sales volumes of other products for the previous months and selected workers on the lowest and highest terciles.

21 The author defines students in the top of the skill distribution as those in the top 50% in debating points in the first baseline round of debates (pre- treatment). He also uses whether students are on a merit scholarship as an additional measure of innate student ability.

Similar to the other studies cited in this section, Dell'Aqua et al. (2024) find that consultants across the skills distribution benefited significantly from having AI augmentation, with those below the average performance threshold increasing by 43% and those above increasing by 17%, compared to their own scores. Nevertheless, for a task selected to be outside the frontier, consultants using AI were19 percentage points less likely to produce correct solutions compared to those not using it. Thus, the authors note that "this generation of LLMs are highly capable of causing significant increases in quality and productivity, or even completely automating some tasks, but the actual tasks that AI can do are surprising and not immediately obvious to individuals or even to producers of LLMs themselves. Because this frontier is expanding and changing, the overall results suggest that AI will have a large impact on work, one that will increase with LLM capabilities, but where the impacts occur will be uneven." As Ekkehard Ernst states,22 "to be able to use these tools responsibly, therefore, requires to learn not only how to use these tools but—importantly—to understand their limitations."

All in all, the existing literature includes seminal contributions like those referenced above. Even though AI is expanding rapidly, it is still in its preliminary stages, leaving many questions unanswered. The interplay between the nature of tasks and LLM capabilities will likely determine how complementary or substitutable the new technology is for low- and high-skilled workers, thereby influencing its potential distributive effects. Experimental evidence models are so specific and focused that their results are hard to generalize. Whether these findings can be generalized to the labor market at large remains an open question.

Last, to gain a more complete understanding of AI's potential local impacts, gathering more specific evidence from developing countries is vital. The constraints involved in these countries— including access to technology and internet, skills endowments, and regulations—must also be further addressed.

22 See https://medium.com/@ekkehard_ernst/the-future-of-digital-skills-c98714e51e75.

VI. Discussion, policy implications, and future research agenda for developing countries

6.1 General discussion

As seen throughout this review, the incipient literature studying the impacts of AI on employment provides some powerful insights but leaves many questions unanswered. Traditional models are so broad that they have difficulty incorporating the specificities of new technologies, bottlenecks to their adoption, and differences between workers who perform a specific occupation or task. In contrast, the newest experimental evidence models are so specific that their conclusions are very difficult to extrapolate to the labor market as a whole. In addition, none of these models can predict how results might change if we allowed these analyses to model worker mobility in a digital and globalized world. In this context, evidence of AI's effects on the division of labor between countries is practically nonexistent, and its effects, such as new forms of offshoring, are still being pondered. Whereas AI is being integrated into businesses around the world at a remarkable speed, evidence to inform the policies is in its early stages of development, and its maturation process is much slower than the changes we are experiencing.

As Acemoglu (2022) notes, "AI is not the first technology with the potential to be transformative and at the same time increase inequality. If we learn from the past, we can shape the future of AI through a better understanding of how and why we have been successful in generating shared prosperity from other major technological breakthroughs." Nevertheless, and from a developing country perspective, the experience of previous industrial and technological revolutions also teaches us that firms and countries that adopt new technologies the fastest are those that obtain the most growth opportunities. These episodes were marked by significant divergence in income, productivity, and well-being between countries, and GenAI might not be an exception (Albrieu et al., 2018g). According to Chan et al. (2021), the players responsible for developing and implementing AI systems will be the ones to largely profit from the system.23 If

23 According to the United Nations and International Labour Organization (2024), "from 2008 to 2017, total venture capital flows to emerging markets, excluding China and India, amounted to just $24 billion, while the United States alone attracted $694 billion during the same period. The disparity in data centre construction is unambiguous, with the US having built 19 times more leading cloud and co-location data centres than India, which has the most data centres among emerging-market economies."

these players are predominantly located in developed countries, a disproportionate share of economic benefit will accrue to these nations, exacerbating wealth inequality between countries. There are obvious and advantageous conditions in developed countries for AI development, including the abundance of capital, the existence of well-funded and high-quality research institutions, and the availability of appropriate infrastructure. The adoption of AI technologies is also fostered in these countries by their accumulation of human capital.

However, AI brings some distinctive opportunities for developing countries. Many of them, for example in Africa, have a young population, which is the most plastic and malleable to adapt to future successive technological changes. At the same time, as discussed in Appendix 1, AI has the potential to increase the productivity of individuals in underdeveloped regions by facilitating access to education, health care, credit, better agricultural management, and more efficient governments. In this context, new technologies can equip workers with tools to navigate this new era in a more advantageous and competitive position than in previous ages.

To take advantage of these opportunities, developing countries must include harnessing the potential of AI as a priority in their agendas and develop a research agenda. According to Albrieu (2022), the most dangerous scenario for developing countries is the status quo: a situation where technology takes too long to penetrate and spread throughout businesses and homes. Failure to adapt the future of work conceptual framework to local realities could result in placing too much concern on nonpriority issues and, worse, overlooking important policy issues.

As noted by De Bastion and Mukku (2020), the first step for developing countries attempting to navigate the digital shift is to improve access and skills. The next step is to build a digital economy that is inclusive and protects citizens' fundamental rights. All this needs to be achieved through constant dialogue and active participation in international discussions to avoid being left behind and uninformed about the actions of leading countries. Finally, it is imperative to develop a research agenda from the South, with policy implications tailored to the region's specific needs. In this sense, we propose five major policy guidelines for developing countries: 1) focus on skills, 2) ensure infrastructure readiness to access new technologies, 3) establish regulations and social protection for web-based platform workers, 4) include developing countries in global arenas where AI ethics and regulation issues are discussed, and 5) set a research agenda for developing countries.

6.2 Policy guidelines for developing countries

6.2.1 Focus on skills

Although the ultimate effects of new technologies on jobs are difficult to predict because they depend on how the technology is adopted, there are some things we know for certain, and one is that those who have the skills and knowledge complementary to new technologies will benefit the most. It is crucial to prepare the population to navigate a fast-moving tech landscape.

Regarding specific skills, as reviewed by Stropoli (2023),[24] the International Society for Technology in Education, a nonprofit that works with educators around the globe, suggests that education on AI should start as early as kindergarten, across all subject areas. Additionally, whatever sector workers are employed in, they will need to have at least basic knowledge of AI to compete in the coming decades, as well as a strong STEM foundation. According to Okolo (2023), while some efforts have been initiated in developing countries to incorporate AI education, they are still in the early stages of implementation.[25] To accelerate and enhance these efforts, partnering with universities and international organizations could be crucial in building the necessary educational and training capacity (UN & ILO, 2024).

On the other hand, and as discussed at the event on AI's impact on the African job market mentioned in Section 3,[26] critical thinking is one skill that will be crucial in this new era. One of the panelists mentioned that in one of his former jobs he had to teach people how to Google, as it was a skill that not many had. These requirements will intensify with new GenAI tools and the need to write good prompts to obtain the right answers. Regardless of what GenAI holds for the future, there will still be a need for interpretation, and this distinguishing aspect will remain a human factor. Nevertheless, and as stated in Section 2, while the reform of study plans must

24 See https://www.chicagobooth.edu/review/ai-is-going-disrupt-labor-market-it-doesnt-have-destroy-it.

25 The author states that "some early efforts have been seen in Kenya, where the government's Digital Economy Blueprint focuses on to incorporating topics in computer literacy, ICT skills, coding, digital citizenship, and online safety into K-12 curriculum. In other developing countries, plans to implement educational upskilling have been noted in digital transformation initiatives from Brazil, Costa Rica, India, Jamaica, Malaysia, Panama, Rwanda and South Africa."

26 For more information, see https://jacobsladder.africa/ai-impact-on-the-african-job-market-x-space/.

be addressed, new elements of analysis—low coverage, poor quality, scarce funding—need to be considered for developing countries.

Last, in an era where technology is moving at unprecedented speed and people live longer, the need for reskilling and upskilling is all the more important. Stropoli (2023) cites several reskilling programs in Denmark for workers injured on the job or displaced due to offshoring that proved successful, and provides some examples of retraining programs in the UK and in US companies for workers displaced by AI and automation. Again, these recommendations must be adjusted to the realities in developing countries, where many workers are self-employed, work in family-based enterprises, or in the less regulated informal sector. Thus, the challenge lies not only in identifying suitable reskilling and upskilling programs but also creating a strategy to include informal workers in developing countries within the broader education framework.

6.2.2 Ensure infrastructure readiness to access new technologies

We have reviewed the potential productivity-enhancing effects that can be achieved with AI and GenAI tools, but as described in Section 2, in some developing countries a large share of their population lacks access to a computer, the internet, or even electricity. Digital infrastructure is a crucial determinant of ICT adoption, and for workers and companies to effectively participate throughout the AI value chain, developing countries must have the appropriate digital infrastructure. In some countries, barriers to participating in AI are present even for individuals working as data labelers. According to Chan et al. (2021), in addition to access to computer devices and connectivity, the method of payment for data labeling services on some of these platforms is also a barrier. "For example," the authors note, "Amazon Mechanical Turk, a widely used platform for finding data labelers, only allows payment to a U.S. Bank Account or in the form of an Amazon.com gift card (Amazon 2020). These methods of payment restrict may not be what is desired by a worker, and can serve as a deterrent to work for this platform."

De Bastion and Mukku (2020) put forward several strategies for promoting access and infrastructure development in developing countries. Some of these include national broadband policies, community-owned networks, the involvement of big tech companies in large-scale developments of internet backbone infrastructure, and making mobile devices, hardware, and internet connectivity affordable. In turn, the UN and ILO (2024) suggest starting with meaningful connectivity and strategic investments in data centers and cloud computing facilities to provide the necessary infrastructure for AI development and deployment; promoting open data policies to make public sector data available for research and development in AI while ensuring privacy and safety; and engaging in international collaborations to share resources and infrastructure, such as access to high-performance computing facilities and international research networks.

6.2.3 Establish regulations and social protection for web-based platform workers

As noted in Section 4, new technologies allow and encourage new forms of offshoring. The digital platforms that mediate between the demand and supply of workers to perform certain tasks allow this exchange between countries. While working on these platforms provides workers with flexibility, allowing workers with disabilities, caring responsibilities, or those in rural or economically depressed areas to earn an income, they also raise some concerns. Workers often face salaries below the minimum wage, lack labor protections, and are deprived of employer-provided social security benefits, with power largely concentrated in the hands of clients. These risks also affect workers in BPOs in developing countries, where many turn to "microwork" in hopes of escaping poverty, only to find themselves in sectors that offer little to no progression or social protection, as noted by Casilli in a Libération article.[27] According to Berg et al. (2019), the issue extends beyond the legal classification of workers; it involves ensuring proper minimum wages, social insurance, anti-discrimination, and safety regimes—all of which vary widely across national jurisdictions. The authors note that "some advocates for crowdworker rights are concerned that if national standards are raised in some countries, platforms would slow or stop accepting workers from those countries."

Recognizing these jurisdictional and regulatory difficulties, the ILO's Global Commission on the Future of Work called for the "development of an international governance system for digital labour platforms that sets and requires platforms (and their clients) to respect certain minimum rights and protections" (Berg et al., 2019). An interesting precedent may be that of

27 See https://www.liberation.fr/societe/petites-mains-de-lia-dans-les-pays-du-sud-il-ny-a-pas-de-carriere-pour-un-microtravailleur-ou-un-moderateur-20240320_FHH32J7IFRAHJKWI2TPXLUUZQU/.

maritime workers who carry out their tasks overseas and whose country borders are also blurred. In this context, the Maritime Labour Convention, 2006 can inspire the creation of legislation that addresses these challenges, with the goal of protecting workers without hindering technological progress.

On the other hand, while AI could eventually boost overall employment and wages, it could put a fraction of the labor force out of work. Yilmazkuday (2024) observes these kinds of displacement effects in the short run and suggests expanded support for workers through additional unemployment benefits. Similarly, in a recent International Monetary Fund (IMF) blog,28 Era Dabla-Norris and Ruud de Mooij note that lessons from past automation waves and the IMF's modeling suggest that more generous unemployment insurance could cushion the negative impact of AI on workers. According to the authors, comprehensive social assistance programs will be needed for workers facing long-term unemployment or reduced local labor demand due to automation or industry closures. As in the case of skilling, innovative approaches will also be needed in emerging countries where workers are less protected by social protection programs associated with formal employment, such as unemployment insurance.

Furthermore, the proponents of the universal basic income argue that this policy may be the answer to the threats of job insecurity and wage inequality induced by AI. Evidence on the potential impacts in both the short and long run is very scarce (see Hoynes & Rothstein, 2019; Daruich & Fernández, 2024). As discussed in Brynjolfsson et al. (2024), portable benefits solutions should also be on the table. The alternative of taxing robots has also been discussed (Costinot & Werning, 2023).

6.2.4 Include developing countries in global arenas where AI ethics and regulation issues are discussed

The exponential growth and adoption of AI brings several issues that are beyond the scope of this review due to prioritization. As previously mentioned, developing countries continue to face significant barriers in adopting AI, including challenges related to skills, infrastructure, and structural hurdles. As noted by Cazzaniga et al. (2024), innovation, regulation,

28 See https://www.imf.org/en/Blogs/Articles/2024/06/17/fiscal-policy-can-help-broaden-the-gains-of-ai-to-humanity.

and ethics can be considered as "second-generation" elements that are likely to maximize the economic impact of AI. These elements have become policy priorities for developed countries.

Even though developing countries must first address skills and infrastructure challenges, they cannot be left out of the global conversation on issues such as informed consent, privacy, data protection, and cybersecurity; fairness to counter algorithm biases; accountability when a recommendation performed by an AI negatively impacts people's lives; environmental aspects; and market competition. If they do not participate in the decision-making areas that shape the future of AI, they will perpetually lag in leveraging its benefits.

6.2.5 Set a research agenda for developing countries

As stated throughout this review, the research agenda on AI is primarily driven by the accumulation of knowledge in the academic hubs of developed countries, which often focus on issues specific to wealthy economies. Extrapolating the conclusions and policy challenges from these studies to developing countries is unlikely to be effective, given their unique characteristics. To fully understand the implications of AI for employment and inclusive growth, it is crucial to develop a research agenda that specifically addresses the unique challenges and opportunities that developing countries face. Moreover, by centering their perspectives and experiences, this research agenda can contribute to a more balanced and equitable global dialogue on the future of work in the age of AI.

The following are key areas for further investigation and analysis:

1. **Impact of AI on labor markets**

    - Further investigate the barriers to AI adoption in developing countries and create models that incorporate these to better predict AI's impact on employment and wages.
    - Develop new methodologies and indicators for measuring AI's impact in developing countries, accounting for the limitations of existing data sources and specific local contexts.
    - Study the gendered dimensions of AI's impact on the labor market.

2. Sector-specific case studies
    - Conduct in-depth case studies on the implementation and effects of AI applications in key sectors of developing economies, such as agriculture, manufacturing, the service sector, and the informal economy.
    - Identify best practices and lessons learned from successful AI adoption in developing countries, highlighting the role of public-private partnerships, local innovation ecosystems, and international collaboration.
3. Global value chains and trade in AI
    - Map the participation of developing countries in global value chains related to AI, including the production of hardware, software, and data labeling services.
    - Analyze the implications of AI for international trade patterns and the competitiveness of developing countries in the global economy, considering factors such as intellectual property rights, data flows, and technical standards.
4. Skills development and workforce readiness
    - Assess the current state of digital skills and AI-related capabilities in the workforce of developing countries, identifying gaps and areas for improvement.
    - Explore innovative approaches to skills development, such as online learning platforms, coding bootcamps, and industry-academia collaborations, that can scale up workforce readiness efforts in resource-constrained environments.
    - Explore ways to include informal workers in upskilling and reskilling initiatives.
5. Current state of labor market policies in the region and best practices
    - Explore the implications of AI on social protection needs and the design of systems that can address the new forms of vulnerability induced by technological changes.
    - Explore opportunities for formalization pathways.
    - Analyze the growth of digital labor platforms and BPOs in developing countries,

the bargaining power of workers in these platforms, and possible recommendations for regulating this work and ensuring fair labor standards, drawing on international best practices and the specific needs of workers in developing countries.

6. AI governance and policy frameworks

    - Assess the current state of AI governance and regulation in developing countries, identifying gaps and areas for improvement in areas such as data protection, algorithmic transparency, and ethical guidelines.

All in all, expanding AI ecosystems in developing countries as autonomous and genuine investments requires a multifaceted strategy. This strategy should not only address financing and infrastructure issues but also include compensatory policies for those adversely affected, training and skill formation policies, and adequate regulations to cope with the economic, social, and ethical risks involved. Building local AI capacity is an ambitious goal that likely requires equitable international partnerships to overcome the significant technological gap between developed and developing nations. Moreover, the increasing availability of this technology presents real opportunities for growth and job creation in these economies. However, realizing these benefits depends on the development of region-specific analyses and policy initiatives. It is crucial that the global conversation on AI incorporate the visions and interests of both developed and developing countries, aiming to promote an AI evolution that contributes to the global well-being.

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Appendix 1.

Potential for GenAI productivity augmentation in developing countries

Regarding education, LLMs can help bridge education gaps by enabling students in remote areas to access high-quality educational content. By implementing LLM-powered solutions, schools in remote areas could also provide personalized learning experiences tailored to each student's needs, as well as offer additional support outside of the classroom through AI-driven tutoring services. For instance, Choi et al. (2024) study how GenAI systems can be integrated into school systems in low-income countries. They introduce an AI chatbot designed to aid teachers in Sierra Leone with professional development by improving lesson planning, classroom management, and subject matter expertise. Meanwhile, as reviewed by Okolo (2023), AI tools have been used to identify at-risk students in Colombia, enhance English learning in Thailand, and develop teaching assistants for science education in West Africa. Another development is by Butgereit and Martinus (2023), who launched a WhatsApp bot that connects students to university-level math tutors via GPT-4, specifically designed for Arabic-speaking regions experiencing periods of violent unrest.

Other examples include agriculture and health care. As stated by Cazzaniga et al. (2024), "in agriculture, AI could be leveraged to predict yields, optimize irrigation, and identify potential pests, thereby enhancing food security and productivity" to benefit the socially and economically vulnerable. Moreover, "in health care, AI could assist in predictive analytics to foresee outbreaks, optimize resource allocation in hospitals, facilitate diagnoses, and make quality health care accessible and affordable even in areas with shortages of qualified medical staff." Additionally, Okolo (2023) documents examples of adopted AI tools in agriculture and health in developing countries.29

In terms of financial inclusion, AI can enhance it by either using unconventional data to

29 Okolo (2023) notes that "within agriculture, projects have focused on identifying banana diseases to support farmers in developing countries, building a deep learning object detection model to aid in-field diagnosis of cassava disease in East Africa, and developing imagery observing systems to support precision agriculture and forest monitoring in Brazil. In healthcare, projects have focused on building predictive models to keep expecting mothers in rural India engaged in telehealth outreach programs, developing clinical support tools to combat antimicrobial resistance in Ghana, and using AI models to interpret fetal ultrasound in Zambia."

evaluate creditworthiness (Bakovic et al., 2020) or demystifying complex financial concepts and providing customized financial support to disadvantaged groups. For instance, in Nigeria, Olubayo Adekanmbi of Data Science Nigeria is developing a multilingual, voice-based chatbot that, among other things, will be capable of recording transactions from verbal inputs, such as "I bought four oranges at N50 naira," and answering financial questions.30 Similarly, Trustt Inc., a SaaS Digital Banking startup, launched a banking product that provides an easy-to-use conversational interface in all 12 Indian languages.31

Finally, new technologies can improve the delivery of social services. For example, Aiken et al. (2022) show that data from mobile phone networks can improve the targeting of humanitarian assistance. Specifically, they use traditional survey data to train machine-learning algorithms to recognize patterns of poverty in mobile phone data; the trained algorithms can then prioritize aid to the poorest mobile subscribers. According to the authors, relative to the geographic targeting options considered by the government of Togo, the machine-learning approach reduces errors of exclusion by 4%–21%. Building on this potential, Cazzaniga et al. (2024) note that "AI could amplify this wave of transformation by assisting in informed decisionmaking, identifying service gaps, detecting fraud and corruption, and customizing local interventions."

30 See https://gcgh.grandchallenges.org/grant/leveraging-large-language-model-llm-financial-inclusion.

31 See https://medium.com/@trustt.tribe/revolutionizing-lending-with-generative-ai-unlocking-financial-inclusion-82a2aae87d4f.

Appendix 2.

Impacts of labor-substituting automation technologies pre-AI

The canonical model that links technological change and labor inequality is based on two types of work—skilled and unskilled—and the assumption of complementarity between skilled work and technology. Building on the pioneering work of Tinbergen (1975), technological advances have increased the demand for skilled workers, thereby raising their market price and exacerbating income inequality. This phenomenon, known as skill-biased technological change, has been instrumental in helping us understand why inequality disparities have widened in developed countries (Katz & Murphy, 1992; Carneiro & Lee, 2009; among others). However, this framework has appeared less applicable in other contexts (Goldin & Katz, 1998). In response, more recent studies have refined this analysis by distinguishing between competencies and tasks (the task-based approach). While competencies are attributes of workers, tasks are associated with specific occupations. The task-based approach provides a framework for studying automation processes, including the digitalization and robotization of certain tasks (Autor et al., 2003; Acemoglu & Autor, 2011; among others), and has become the preferred model in economics for studying AI's impact on labor markets.

In this framework, routine tasks—both cognitive and noncognitive—are more likely to be automated, leading to a drop in labor demand for these types of tasks, which are usually performed by middle-skilled workers who earn medium wages. In this context, technology increases the weight of two groups of workers: those working in occupations that require intensive nonroutine cognitive tasks and those in occupations requiring intensive nonroutine, noncognitive tasks. While the first group is associated with high levels of productivity and income, the second is associated with low levels of both. These shifts in the demand for workers are known as the employment polarization hypothesis (Autor & Dorn, 2013; Goos et al., 2014). This hypothesis is supported by numerous studies that have shown the relationship between automation technologies and wage inequality in the US, particularly through relative wage declines for workers specializing in routine tasks (Autor et al., 2006; Van Reenen, 2011; Acemoglu

& Restrepo, 2022).

Methodologically, to study the effect of technological innovation on the labor market, many studies have followed the approach of Frey and Osborne (2017). This approach consists of conceptualizing individual occupations as a bundle of tasks and considering which tasks can be replaced or complemented by technology, which allows the classification of occupations according to their risk of automatization. For this categorization, the studies rely on AI and on the use of experts who examine occupation by occupation. Artnz et al. (2016) follow a similar approach but incorporate individual survey data on a comprehensive list of tasks that people perform at their workplace, recognizing that individuals within the same occupation often perform quite different tasks. According to Fray and Osborne, around 47% of total US employment is susceptible to computerization, whereas Artnz et al. (2016) find that the risk is 9%.

Most of these studies center on the US, using the O*NET classifications and descriptions for each occupation, though the methodology has also been adapted to account for the occupational structures of other countries. It is important to highlight that the methodology focuses on the technical capability of substitution rather than its economic feasibility; thus, the relative price of human labor versus machines is not considered.

Regarding developing countries, Brambilla et al. (2023) use the two methodologies—by occupation and by task—to examine the risk of automation in Latin American economies. They find that the most significant impact of automation would fall on unskilled and semi-skilled workers, with skilled labor remaining largely unaffected32. The authors conclude that automation is a more serious threat to income equality than to employment in general.

Similarly, Weller et al. (2019) estimate the risk of technological substitution of human labor based on the Frey and Osborne (2017) methodology but adjust for the structural characteristics of Latin American labor markets. Specifically, they consider two factors: 1) the

32 It should be noted that a previous study had already indicated that recent changes in labor markets in the region were more consistent with the traditional hypothesis of biased technological change than with the polarization hypothesis (Gasparini et al., 2020).

segmentation of Latin American labor markets, with large sectors of low productivity that would not be largely affected by technological advances, and 2) the lag in the implementation of new technologies in the region compared to the developed world, which affects even medium- and high-productivity sectors). While around 62% of occupations are at risk of replacement with the original methodology, this figure drops to 24% when adjustments are made to account for the structural conditions of the region's labor markets.

According to Weller et al. (2019), many of the jobs that will not be replaced are of the lowest quality. This lower level of automation risk in the region, compared to developed countries, reflects the persistence of low-productivity sectors, where workers maintain subsistence-level livelihoods and have very limited capacity to adopt new technologies. As Weller (2020) notes, Latin America's low wages mean that significant productivity gains, derived from technical change, would be needed to make substitution profitable. This creates a paradox, one that may extend to other developing countries: the lower risk of job loss stems from challenges in adopting new technologies, which in turn hampers productivity growth. In fact, and in contrast to evidence found for countries like the US, over the last two decades, wage inequality fell everywhere in LAC (Gasparini, 2019). According to Weller et al. (2019), "to the extent that only a small subset of firms have so far adopted new skill-intensive technologies, the demand for workers with more years of schooling (relative to that with fewer years) has not been substantially stimulated, at least not enough given the regions' efforts to expand secondary and tertiary education. Other factors, some international and some domestic, have played a much more important role than new technologies."

Appendix 3.

Differential impact of AI on men and women

Despite progress, women continue to face disadvantages in the labor market. They have greater difficulties in obtaining quality jobs and are more likely to experience unemployment and informality. The literature on gender differences has coined metaphoric names to some of these issues, such as glass ceilings, sticky floors, and leaky pipelines. Another metaphor, glass walls, highlights the invisible barriers or obstacles that hinder or prevent women from participating in dynamic and better-paid economic sectors, which historically were, and continue to be, occupied by men. According to Bustelo et al. (2019), nearly 30% of women in LAC work in care-related sectors (e.g., education, health, and domestic work), compared to only 6% of men. Additionally, almost 30% of all female workers are employed in service sectors related to commerce, the hotel industry, or food services, versus 20% of all male workers.

Naturally, if women perform different tasks and work in different sectors than men, their exposure to AI would be different, according to the models reviewed in Section 5. Using a task-based approach, Bustelo et al. (2019) find that women are underrepresented in STEM occupations, and 23% of women and 16% of men face a risk of automation in LAC, given that the tasks replaced by technology are those performed to a greater extent by women. Cazzaniga et al. (2024) also find that exposure to AI is higher for women but is mitigated by a higher potential for complementarity with AI. In this context, in most countries women tend to be employed in high-exposure occupations more than men. Because this share is distributed approximately equally between low- and high-complementarity jobs, the result can be interpreted to mean that women face both greater risks and greater opportunities.

In addition to examining the tasks that women perform, it is important to understand how they are equipped to face this new era. Despite advances on a global scale, a gender digital divide remains. According to the International Telecommunication Union,[33] 62% of men use the internet, compared to 57% of women. These figures worsen when looking at lower-income

[33] For more information, see https://www.itu.int/itu-d/reports/statistics/2023/10/10/ff23-the-gender-digital-divide/.

regions. For example, only 20% of women in low-income countries used the internet in 2023, compared to 80% and 93% in upper-middle-income and high-income countries, respectively.

Similar gaps exist in education and skills. For instance, although women make up over half of higher education enrollments in Argentina, Brazil, and Mexico, they represent less than 30% of students in engineering and applied science, and less than 15% in careers ICT-related fields (Szenkman et al., 2021). Worldwide, women represent only 12% of AI researchers and 6% of software developers (EQUALS, 2019).

The low representation of women in AI decision-making areas comes with important challenges. According to Szenkman et al. (2021), the lack of diversity in the creation and use of algorithms has serious risks of exacerbating preexisting biases and stereotypes. Gender bias in AI is amplified in numerous ways, including during an algorithm's development process, in the training of datasets, and in AI-generated decision-making. One example is the personnel selection algorithm that Amazon developed in 2014 and then eliminated shortly after due to it showing a strong gender bias. This was because the algorithm was trained with 10 years of data from previous applicants, who were mostly male. Thus, the algorithm chose the most successful workers in the company, who were predominately men, and leading it to incorrectly learn that CVs belonging to men were superior. The European Union's law enforcement agency predicts that as much as 90% of content on the internet could be created or edited by AI by 2026, meaning the impact of gender bias in AI is only set to grow.34

In parallel, and conversely, there are venues by which AI can be used to reduce existing biases, such as cultural biases that prevent women from studying STEM careers, to cite only an example. For instance, as Bao, Huang, and Lin note,35 gender-related variables can be removed from AI input to enhance gender neutrality in classrooms.

34 See https://www.devex.com/news/how-can-the-un-s-new-advisory-body-on-ai-help-drive-gender-equality-106930?utm_source=devex&utm_medium=email&utm_campaign=devex_social_icons.

35 In their study, the authors analyze data from an experiment where AI replaced a random subset of human teachers at a training agency for Go, an abstract strategy board game for two players. They observe a persistent gender performance gap before the experimental intervention, with boys performing significantly better than girls. After introducing AI, they find that both genders in the treated group progressed faster than their counterparts in the control group, with girls advancing more rapidly than boys under AI training. For more information, see https://voxdev.org/topic/education/improving-learning-efficacy-and-equality-ai-training.

In short, women face particular challenges and opportunities when it comes to AI. Many are associated with a long cultural heritage that propels women to work in sectors more related to care or to be less represented in decision-making positions. The final outcome will depend on how quickly women can acquire skills complementary to new technologies and gain access to digital infrastructure, enabling them to harness AI for their benefit. It will also depend on their representation in decision-making roles within AI-related fields, which are becoming major levers of global influencers.