

# Work, technological transition, and digital skills

## Work in Brazil: Adoption of digital technologies and Artificial Intelligence

*By Manuela Cortez da Cunha Cruz<sup>1</sup>*

The use of information and communication technologies (ICT) has become consolidated in the labor market, with more and more people and enterprises adopting these technologies in their daily lives (NIC.br, 2025, 2026). Today, work routines can also involve using the Internet in different tasks such as sending emails and instant messaging, creating online documents, promoting and selling products, and using Artificial Intelligence (AI) tools. The literature maps how this transformation is occurring and indicates its impacts (Acemoglu & Restrepo, 2019), especially in high-income countries, where digitalization was rapid and with high rates of job reallocation, replacement, and/or job extinction. However, in low- and middle-income countries, there is still

little understanding of how this increasing (albeit slow) exposure to emerging technologies has impacted the labor market (International Labour Organization [ILO], 2025).

Comin (2023) points out that, in countries like Brazil, when the digitalization's impacts reach the population, they tend to be more intense in the intermediate strata of the workforce. Brazilian data from the ICT Households survey, produced by Cetic.br (NIC.br, 2025), in line with the ILO (2025), demonstrates that broad access to and adoption of technologies by the population as a whole does not immediately translate into incorporation of these technologies into work routines. The survey data show a significant increase in Internet access and frequency of use among the Brazilian population over the past ten years (between 2015 and 2025). In 2015, 58% of the population aged 10 years or older were Internet users, while in 2025, Internet users represented 85% of the population (Chart 1).

Conversely, although the absolute number of people using the Internet for work-related activities increased, the proportion of Internet users who used it for work remained stable between 2015 and 2025 (Chart 2). In absolute terms, this represents

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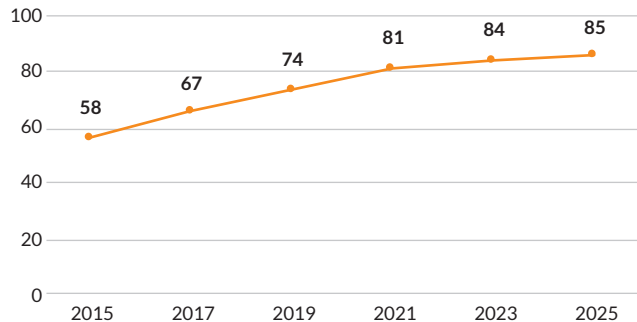
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an increase of more than 20 million people using the Internet for work activities in Brazil. However, because the overall Internet-user population grew by more than 50 million during the same period, the share of users who go online for work did not change significantly.

**Chart 1 – INTERNET USERS IN BRAZIL (2015, 2017, 2019, 2021, 2023, 2025)**

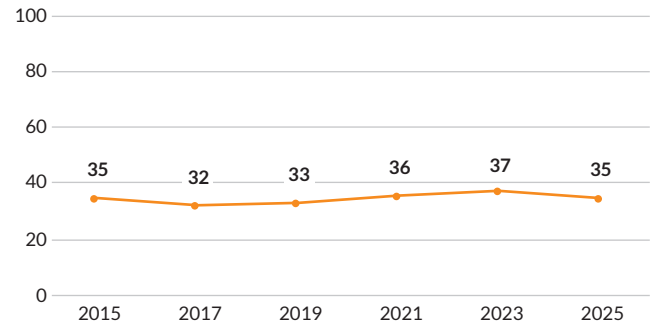
Total population (%)



Source: NIC.br (2016, 2018, 2020, 2022, 2023, 2025).

**Chart 2 – INTERNET USE FOR WORK-RELATED ACTIVITIES (2015, 2017, 2019, 2021, 2023, 2025)**

Total number of Internet users (%)



Source: NIC.br (2016, 2018, 2020, 2022, 2023, 2025).

The ICT Households 2025 survey also indicated that, among workers,<sup>2</sup> 47% used the Internet for work (NIC.br, 2025). Based on data, the following sections present an analysis of the use of technologies at work and as a form of productive inclusion in Brazil. Three variables are considered for this purpose: Internet use for work, AI use for professional or work-related activities, and Internet use to sell or advertise goods and services. Finally, there will be a brief discussion of digital skills required in the labor market.

## The use of the internet for work

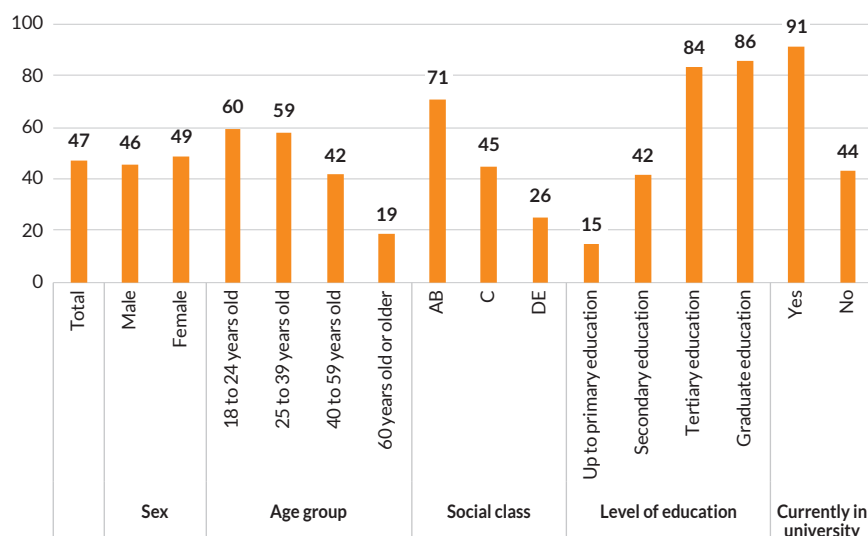
In 2025, the results of the ICT Households survey (NIC.br, 2025) showed that some socioeconomic factors are associated with Internet use for professional or work-related activities. In Chart 3, the data by age group show that the younger generations (18 to 24 years old and 25 to 39 years old) are the most likely to use the Internet at work. This aligns with Prytkova et al. (2025), who highlighted that these groups experience positive impacts associated with new technologies, while labor market adjustments related to innovation are also linked to the gradual entry of new generations into the labor market. In contrast, only 19% of workers aged 60 or older used the Internet for work, a population that tends to face more significant limitations in technological transition processes, due to both adaptation challenges and difficulties in acquiring new skills, which can hinder re-employment and reintegration into the labor market (Cazzaniga et al., 2024).

<sup>2</sup> Economically active population (PEA) that works in paid or unpaid activity (NIC.br, 2025).

Still regarding age, young people and those with a Tertiary Education tend to face fewer difficulties adapting and entering jobs transformed by technological transitions (Cazzaniga et al., 2024); the data also indicate greater use of the Internet for work among these groups. People with Tertiary Education (84%) and postgraduate education (86%), as well as university students (91%), showed the highest proportion of Internet use for professional activities.

**Chart 3 – INTERNET USE FOR PROFESSIONAL OR WORK-RELATED ACTIVITIES AND THE SOCIOECONOMIC DIMENSION IN BRAZIL (2025)**

Total number of workers (%)



Source: NIC.br (2025).

Data from the ICT Households survey also demonstrates that social class is associated with the use (or non-use) of the Internet for work-related activities. Chart 3 shows that more than half of individuals in social classes AB (71%) use the Internet for professional or work-related activities. In contrast, in social classes DE, 26% of the population uses the Internet for these purposes. This may be because people in these classes tend to hold jobs that require physical effort and intensive use of sensory and motor functions (such as construction, agriculture, and domestic services), which are typically associated with low wages and informal work relationships (Comin, 2023).

Chart 4 shows lower Internet use for work among informal workers (34%), suggesting that those in more precarious employment ties, such as informal workers and unpaid family workers, face specific challenges amid technological transformation. As the ILO (2025) notes, the impacts of emerging technologies on work are not uniformly distributed across occupations and may result in both the transformation of activities and work relationships and different levels of exposure to automation.



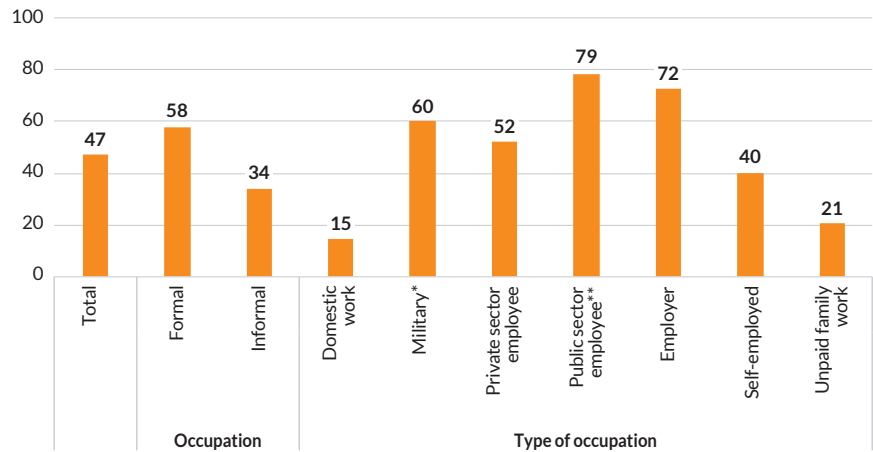
Photo: Personal archive

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Cetic.br|NIC.br

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**Chart 4 – INTERNET USE FOR PROFESSIONAL OR WORK-RELATED ACTIVITIES, BY OCCUPATION (2025)**

Total number of workers (%)



\*Military personnel of the Army, Navy, Air Force, Military Police or Military Fire Department.

\*\*Public sector employee (including mixed-economy enterprises).

Source: NIC.br (2025).

The ability to take advantage of these opportunities also varies according to workers' occupational position. Data from the ICT Households 2025 survey showed that Internet use at work varied significantly by occupation, with higher proportions among public sector employees (79%), employers (72%), military personnel (60%), and private sector employees (52%). In contrast, domestic workers (15%) and unpaid family workers (21%) had the lowest percentages, while 40% of self-employed workers used the Internet in their professional activities. In this context, understanding the relationship between emerging technologies and the Brazilian labor market requires consideration of its structural characteristics, such as the heterogeneity of forms of occupational insertion, high informality, and high turnover. These factors affect different groups of workers unequally, contributing to the persistence and deepening of social inequalities (Inter-American Development Bank [IDB] et al., 2026).

## Use of ai for work

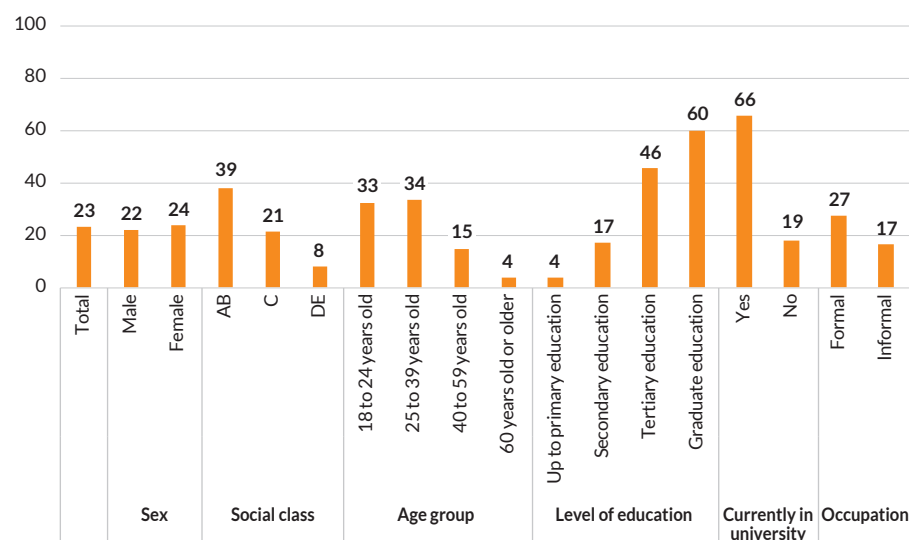
The ICT Households 2025 survey was the first in its history to measure AI use among the Brazilian population,<sup>3</sup> based on the variables: (a) use of generative AI tools; (b) use of generative AI, by purpose; and (c) non-use of generative AI, by stated reason. The data reveals that 28% of the Brazilian population said they used some generative AI tools, such as ChatGPT, Copilot, Gemini, or WhatsApp's Meta AI (NIC.br, 2025). Of the total population, only 14% used any of these tools for professional or work activities.

<sup>3</sup> Regarding variables M1, M2, and M3, find out more: <https://cetic.br/en/pesquisa/domicilios/>

David Autor (2024) described AI as a new work tool with the potential to increase the productivity of trained and experienced workers. However, like other technological transformations, AI tends to cause job displacement and automate certain tasks, making some skills obsolete (Autor, 2024; Acemoglu et al., 2026). In Brazil, the ICT Enterprises survey (NIC.br, 2026) shows a gradual increase in the use of AI tools across different activities among Brazilian enterprises; in 2025, 17% reported using AI.

**Chart 5 – AI USE FOR PROFESSIONAL OR WORK-RELATED ACTIVITIES AND THE SOCIOECONOMIC DIMENSION IN BRAZIL (2025)**

Total number of workers (%)



Source: NIC.br (2025).

In Chart 5, it can be observed that, as with Internet use for work, the adoption of AI in work-related activities is also unequal among different social groups of workers. Among the factors analyzed, differences in AI use for professional activities by social class and education level stood out. Use was highest among workers in classes AB (39%), decreasing to 21% in class C and only 8% in classes DE. Higher adoption was also observed among younger people, adults 18 to 24 years old (33%) and those 25 to 39 years old (34%), while the percentage dropped to 15% among people 40 to 59 years old and was even lower among workers 60 years old or older (4%). The association between education level and the use of AI for professional activities was the most pronounced: only 4% of people with up to a Primary Education used AI for work, a proportion that increased to 17% among workers with a Secondary Education, 46% among those with a Tertiary Education, and 60% among people with postgraduate education. Furthermore, usage was particularly high among university students (66%), suggesting the accelerated adoption of these tools within Brazilian universities. Finally, formal workers (27%) used AI more frequently than informal workers (17%), suggesting an association between the appropriation of this technology and the way of entering and accessing the labor market.

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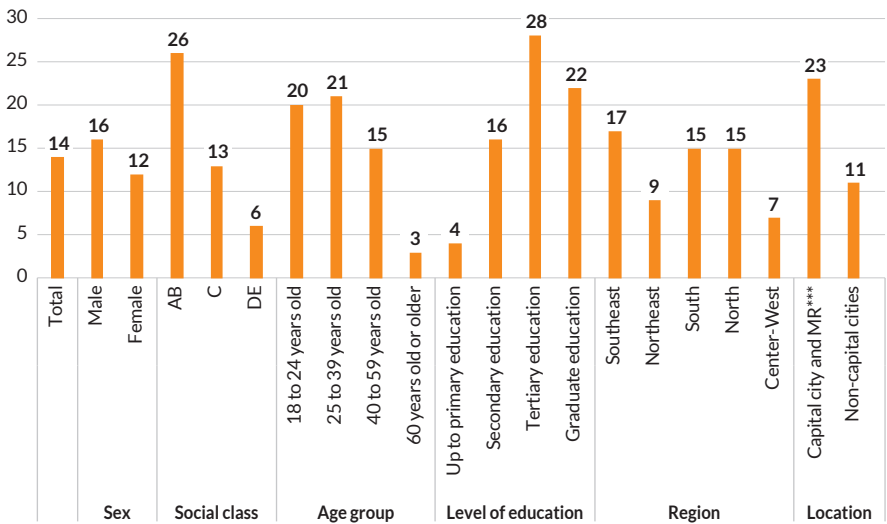
Some of the literature on the topic discusses how advances in automation, digitization, and AI have transformed the labor market, mainly by creating demand for new skills that were uncommon or nonexistent until recently (Acemoglu & Restrepo, 2020; Comin, 2023; Jaumotte et al., 2026). These skills include using cloud computing platforms, data visualization, and analyzing large volumes of information, as well as emerging skills in areas such as information technology (IT), business, administration, and health. These changes, therefore, have altered the nature of occupations, the composition of employment, and wage dynamics (Jaumotte et al., 2026).

## The internet as an opportunity for productive inclusion

Among the various uses of the Internet for economic purposes, its use for advertising or selling goods and services online stands out as an indicator that can provide clues about the potential of using the Internet for increasing income activities or for alternative forms of productive inclusion. As with the other indicators presented, there is great variation among individuals who sell or advertise goods and services on the Internet. In other words, opportunities for productive inclusion through the Internet are not distributed homogeneously across the Brazilian population. The findings of IDB et al. (2026), in agreement with Chart 6, showed that gender differences were significant in the use and marketing strategies: In addition to men selling and advertising more online (16%), they carried out this type of activity in structured marketplaces (such as Mercado Livre and Amazon), which have stronger institutionalization and reach in the digital environment. In contrast, women (12%) predominantly used social networks, which can limit commercial reach to their personal contact networks (IDB et al., 2026).

**Chart 6 – ADVERTISED OR SOLD GOODS OR SERVICES ONLINE AND THE SOCIOECONOMIC DIMENSION (2024)**

Total population (%)

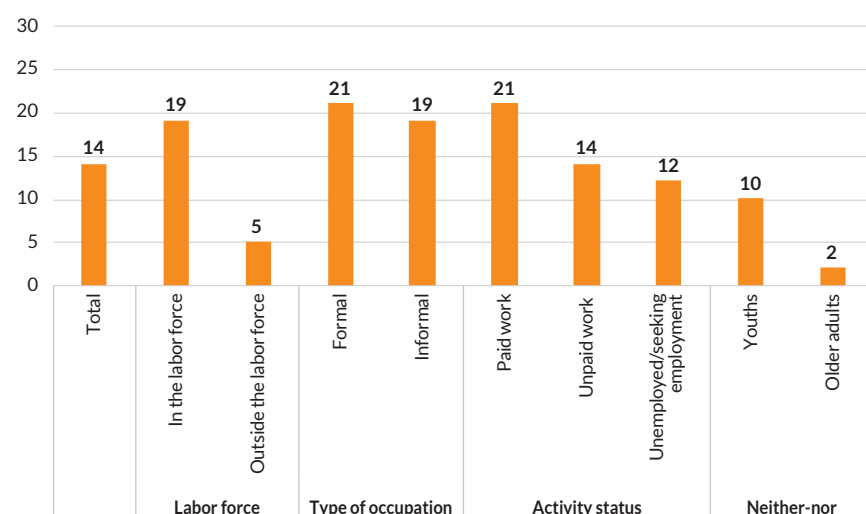


\*\*\*Metropolitan Region.

Source: NIC.br (2024).

In addition to gender differences, regional and territorial factors were also notable in the sale or advertising of goods and services online. Among residents of capital cities or metropolitan regions, 23% engaged in this type of activity, a proportion more than double that observed among residents in non-capital cities (11%). Chart 6 also shows a direct association between the socioeconomic position of individuals and the use of the Internet for selling and advertising goods and services, which was more frequent among people in classes AB (26%), followed by class C (13%), and lower in classes DE (6%).

**Chart 7 – ADVERTISED OR SOLD GOODS OR SERVICES ONLINE, BY WORK INDICATORS (2024)**  
Total population (%)



Source: NIC.br (2024).

According to data from the ICT Households 2024 survey (NIC.br, 2025), using the Internet to sell goods and services can represent a supplement to income, or even an alternative to entering the formal labor market, as shown in Chart 7, especially with regard to activity status. There are important differences by workforce participation: 19% of individuals performed these activities, while the proportion was only 5% among those outside the workforce. Regarding the formality of the occupation, the difference was only two percentage points: 21% of those who work formally and 19% of those who work informally sold or advertised products and services online. Among people in the “neither-nor” categories, those not engaged in productive activities, selling or advertising online also does not seem to be a viable alternative for income access: only 2% of neither-nor older adults<sup>4</sup> and 10% of neither-nor youth<sup>5</sup> advertised or sold goods or services over the Internet.

The data in Chart 7 demonstrates the complexity of the Brazilian scenario: ICT can expand income-generating opportunities, while forms of productive insertion outside the formal labor market can occur without access to social protection systems. In this scenario, Comin (2023) highlighted the need for special attention

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<sup>4</sup> Elderly adults (60 years old or older) who said that they are not working or looking for work and are not retired.

<sup>5</sup> People between 14 and 24 years old who said that they are not working or looking for work and are not attending school or university.

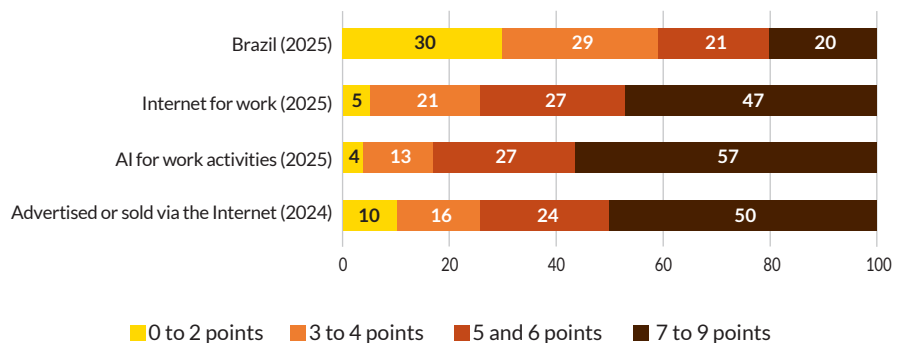
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(...) taking advantage of opportunities offered by digital technologies for professional and work-related purposes is associated with meaningful connectivity. Individuals with better access (...) use the Internet more frequently for work activities, adopt AI tools, and sell and promote products or services online.

to the relationship between work and the social protection system, especially in middle-income countries like Brazil, where the insertion of new technologies into the labor market alters its nature and can lead to a process of de-wage-laborization.

Analyzing Internet use and access in Brazil, especially in the context of work, without considering meaningful connectivity results in an incomplete understanding of the phenomenon. Since 2024, Cetic.br | NIC.br<sup>6</sup> has incorporated this concept into its analyses of digitalization in Brazil to examine how connectivity conditions can enable the exploitation of opportunities while also helping manage and mitigate the potential risks of the virtual world. Chart 8 demonstrates the intersection of meaningful connectivity levels with the three variables presented: Internet use for professional or work activities, use of AI for work, and Internet use to sell or advertise products or services.

**Chart 8 – INTERNET, WORK, AND MEANINGFUL CONNECTIVITY IN BRAZIL (2024 AND 2025)**  
Total population (%)



Source: NIC.br (2024, 2025).

The results presented indicate that taking advantage of opportunities offered by digital technologies for professional and work-related purposes is associated with meaningful connectivity. Individuals with better access, connection quality, equipment availability, and usage environments use the Internet more frequently for work activities, adopt AI tools, and sell and promote products or services online. Although the results are descriptive and do not allow for establishing causal relationships, they suggest that productive inclusion in the digital environment is associated not only with Internet access but also with adequate conditions for its meaningful use.

<sup>6</sup> Find out: <https://www.cetic.br/en/publicacao/conectividade-significativa-propostas-para-medicao-e-o-retrato-da-populacao-no-brasil/>, <https://cetic.br/en/publicacao/ano-xvi-n-3-conectividade-significativa-e-competencias-digitais/>, and <https://cetic.br/en/pesquisa/domicilios/>

## Digital skills in the world of work

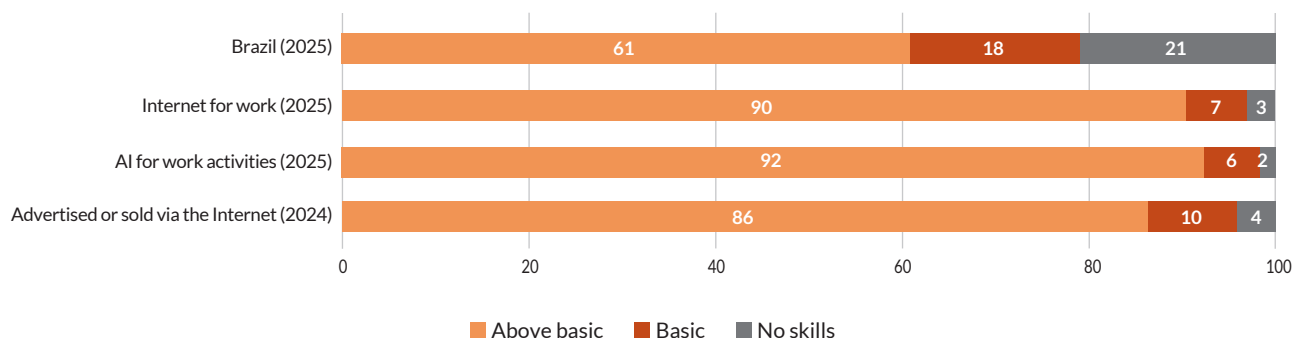
The literature indicates that the labor market is being shaped by the demand for new digital skills, including specific skills related to the introduction of AI in work activities. As with the impacts of digitalization on the labor market, the need for new skills and the ability to meet these demands have also spread unevenly across countries. In countries like Brazil, there are indications that the demand for new skills is also high, but the supply of qualified professionals remains limited (Jaumotte et al., 2026).

The ICT Households survey measures the digital skills of Internet users based on the International Telecommunication Union (ITU, 2020) conceptual framework. The survey assesses skills across five dimensions: information and data literacy, communication and collaboration, digital content creation, security, and problem-solving. These skills are central to understanding how individuals take advantage of Internet opportunities, including access to information, social relationships, and work activities. Charts 9 to 13 relate digital skills<sup>7</sup> to three variables: Internet use for work, use of AI for professional or work-related activities, and Internet use for selling or advertising products and services.

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**Chart 9 – DIGITAL SKILLS AND WORK: INFORMATION AND DATA LITERACY (2024 AND 2025)**

Total population (%)



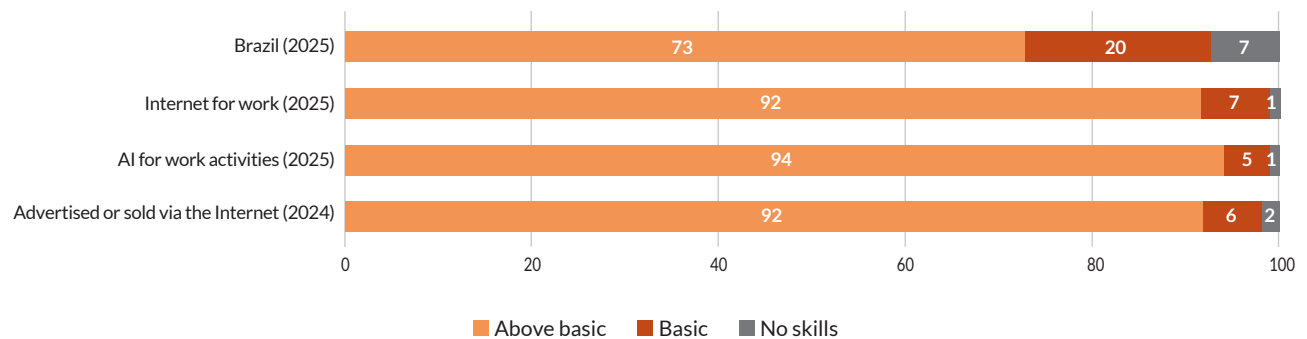
Source: NIC.br (2024, 2025).

<sup>7</sup> The ITU's digital skills indicators consider the activities performed by individuals in the last three months. Basic skills are classified as those associated with performing one activity in a given area, and above-basic skills as those associated with performing two or more activities in the same area. They are grouped into five areas: information and data literacy, communication and collaboration, digital content creation, security, and problem-solving. Find out more: <https://www.itu.int/itu-d/meetings/statistics/wp-content/uploads/sites/8/2023/09/Report-of-the-EGH-subgroup-on-ICT-Skills.pdf>

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**Chart 10 – DIGITAL SKILLS AND WORK: COMMUNICATION AND COLLABORATION (2024 AND 2025)**

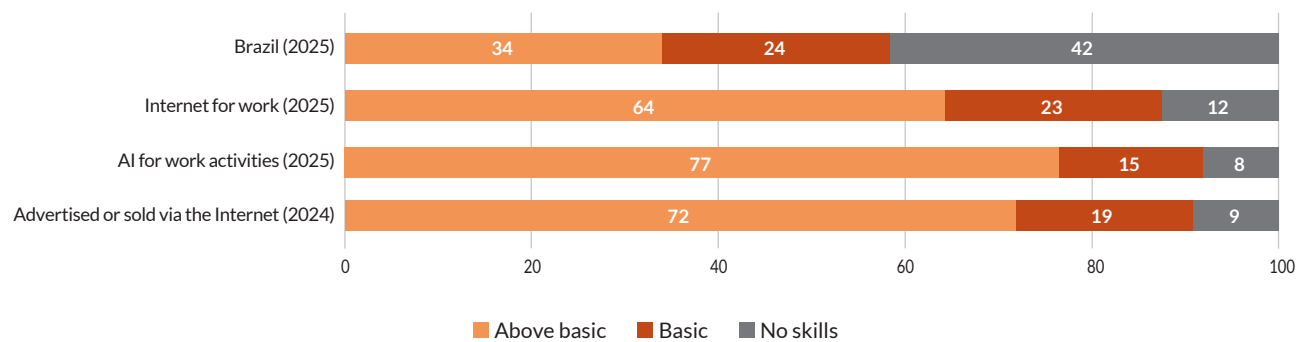
Total population (%)



Source: NIC.br (2024, 2025).

**Chart 11 – DIGITAL SKILLS AND WORK: DIGITAL CONTENT CREATION (2024 AND 2025)**

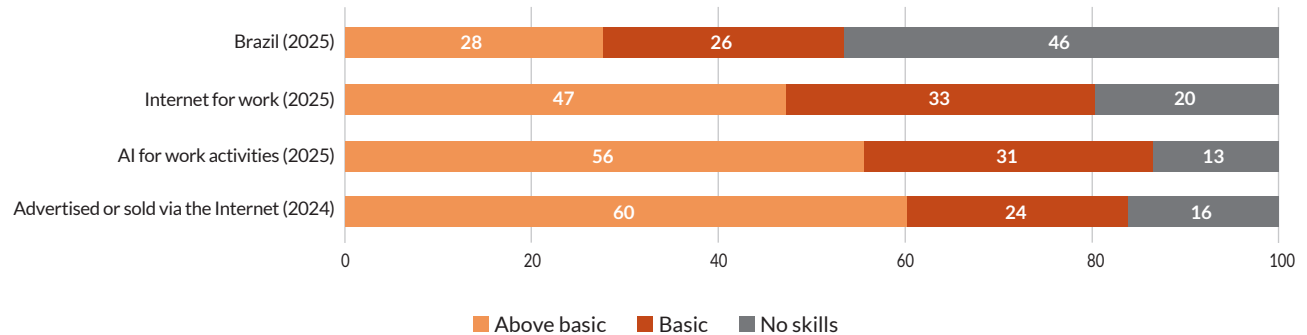
Total population (%)



Source: NIC.br (2024, 2025).

**Chart 12 – DIGITAL SKILLS AND WORK: SECURITY (2024 AND 2025)**

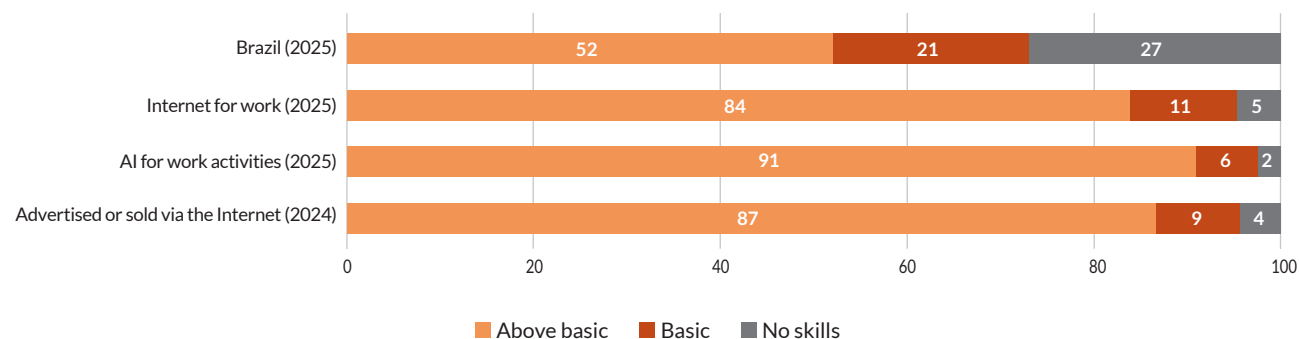
Total population (%)



Source: NIC.br (2024, 2025).

**Chart 13 – DIGITAL SKILLS AND WORK: PROBLEM-SOLVING (2024 AND 2025)**

Total population (%)



Source: NIC.br (2024, 2025).

The data in Charts 9 to 13 shows an association between digital skills and the ability to take advantage of job opportunities and income generation. In all indicators analyzed, individuals who use the Internet and AI tools for professional activities, and for selling and promoting products and services, show higher levels of digital skills than the general Brazilian population. This suggests that digital competencies are fundamental to accessing the economic opportunities provided by digital technologies. In this context, the literature points out that, in countries like Brazil, the improvement of digital skills requires actions and public policies that stimulate the expansion of lifelong learning, the integration of information technology skills in different areas of training, and the strengthening of education in Science, Technology, Engineering, and Mathematics (STEM) (Jaumotte et al., 2026).

The analysis presented offers an initial overview of how the Brazilian population uses digital technologies for productive purposes and highlights both the opportunities and challenges associated with the digital transformation of work. The findings pave the way for future investigations that deepen the understanding of the conditions necessary for digital and emerging technologies, such as AI, to expand opportunities and effectively contribute to productive inclusion in Brazil.

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## Interview I

# New skills and the challenges of work in the age of Artificial Intelligence

In this interview, Marina M. Tavares, senior economist at the International Monetary Fund (IMF), discusses the impacts of Artificial Intelligence (AI) and new skills on work and the labor market, highlighting Brazil's position in this context. She also discusses the effects of AI on wages and employment, the risks of labor market polarization, and the importance of education and workforce reskilling.

***Internet Sectoral Overview (I.S.O.)\_ You recently co-authored the IMF Staff Discussion Note Bridging skill gaps for the future: new jobs creation in the AI age,<sup>8</sup> which argues that new skills tend to emerge first in advanced economies before gradually diffusing to emerging markets. How does this diffusion process take place, and where does Brazil stand in this evolving landscape?***

**Marina M. Tavares (M.M.T.)\_** In our new study, we measure skill diffusion using a large database of online job postings across countries. These postings are particularly useful because they tell us not only which occupations enterprises are hiring for, but also the specific skills employers are looking for. The postings include familiar skills, such as communication and teamwork, but also include very specific and emerging skills—for example, digital tools such as Power BI and Tableau, or new ways of reaching customers through social media platforms such as TikTok and Instagram. Using these data, we can identify when enterprises in different countries start looking for workers with a particular skill, which countries demand it first, and how that demand spreads across countries over time.

What we find is that new skills tend to emerge first in advanced economies, especially the United States, the United Kingdom, and Germany, and then spread to other countries. But this diffusion is fast. When skills spread internationally, it typically happens within a year. Denmark and the United Kingdom tend to start demanding new skills only two to four months after the United States, while in Brazil and South Africa, the average delay is closer to eight or nine months.

So Brazil is best thought of as a relatively fast follower. Our data show that it is more often a recipient of new skills rather than an originator, but the gap in the technological frontier is measured in months rather than years. Importantly, the process is not entirely one-way: We also see some new skills emerging in Brazil and later appearing elsewhere.



Photo: FMI

**Marina M. Tavares**

Senior economist  
at IMF

<sup>8</sup> Available at: <https://www.imf.org/-/media/files/publications/sdn/2026/english/sdnea2026001.pdf>

"AI is also creating valuable new skills, but at the same time, it can carry out some of the cognitive tasks performed by workers. So the same technology can make some workers more productive while reducing the demand for others."

**I.S.O.\_** *The report distinguishes between new skills and AI-related skills. What is the difference between these two concepts, and what do their distinct effects on wages and employment tell us about how AI is changing the nature of work and the labor market?*

**M.M.T.\_** New skills are skills that were barely present in United States job postings at the beginning of the 2010s but have since become much more common. We use the United States to identify these skills because it has the longest time series in our data. New skills cover a very broad range. Some are related to new technologies, but others reflect changes in areas such as health care, business, or energy. Within these new skills, we then distinguish those that are related to AI. Some are skills needed to use AI, such as working with ChatGPT or GitHub Copilot, while others are more technical skills needed to build AI systems, such as Python for machine learning or tools like TensorFlow or PyTorch.

What is particularly interesting is that we can use our data to estimate how the spread of these new skills affects wages and employment across United States local labor markets. For new skills overall, the results are relatively positive. A 1 percentage point increase in the share of job postings requiring new skills is associated with about 2.3% higher average wages and 1.3% higher employment. Skill related to AI tell a somewhat different story. Workers with these skills can earn significant wage premiums in the United States and the United Kingdom, the two countries where our data allow us to estimate them. In the United Kingdom, both AI-user and AI-developer skills are associated with wage premiums of around 7.5% to 8%. In the United States, the largest premium—more than 8%—is concentrated among the more technical AI-developer skills, while AI-user skills carry a smaller premium of about 2%. But we do not yet see the same increase in overall employment associated with the spread of AI skills. And in occupations where AI can perform many of the tasks currently done by workers, and where there is less scope for workers and AI to complement one another, employment has declined relative to other occupations.

To me, this highlights what is distinctive about AI. New technologies have always created demand for new capabilities, and historically that process can generate new jobs as well as higher wages. AI is also creating valuable new skills, but at the same time, it can carry out some of the cognitive tasks performed by workers. So the same technology can make some workers more productive while reducing the demand for others. It is still very early, so we should be cautious about interpreting these effects as permanent. But so far, the evidence suggests that the adjustment to AI may be more disruptive in the short term than the historical gradual introduction of new skills more generally.

***I.S.O\_ Job polarization has become an important concern as new skills are reshaping labor markets. What does this phenomenon mean in practice, what drives it, and how can its effects be mitigated?***

**M.M.T.\_** Economists use the term job polarization to describe a pattern in which employment growth becomes concentrated at the top and bottom of the skill distribution, while opportunities for middle-skill workers weaken. This pattern has been documented extensively in the economics literature, including by Goos and Manning,<sup>9</sup> Acemoglu and Autor,<sup>10</sup> and Autor and Dorn,<sup>11</sup> and has been closely linked to earlier waves of automation and technological change. In practice, technology can raise demand for highly skilled workers, while also increasing demand for lower-skilled service jobs, even as many routine middle-skill occupations come under pressure.

In our study, we can examine whether the current wave of new skills is producing a similar pattern. We first estimate how the arrival of new skills affects wages and employment across United States local labor markets, and then separate those effects across four broad groups of occupations: high-skill occupations, white-collar middle-skill occupations, blue-collar middle-skill occupations, and low-skill occupations. What we find is quite striking. High-skill workers, such as managers and engineers, experience the largest gains. But low-skill workers also benefit. By contrast, the effects for white-collar and blue-collar middle-skill occupations are much smaller and not statistically significant.

High-skill workers tend to benefit directly because many new technologies and skills complement what they already do and make them more productive. The gains for low-skill workers are more indirect. When productivity and incomes rise in the more innovative parts of the economy, high-skilled workers receive higher wages and spend more on services—restaurants, personal care, transportation, and other activities that still rely heavily on human labor. This creates additional demand for lower-skill jobs. The middle is more vulnerable because many of these occupations contain tasks that can increasingly be performed by technology, while workers may not immediately have the skills needed to move into the new high-paying jobs.

Policy priorities include helping workers move from occupations in decline toward new opportunities. That means lifelong learning and retraining that respond quickly to changing skill demand, as well as education systems that give people the cognitive, creative, and technical skills that complement new technologies. It also means reducing barriers to moving across jobs and regions, for example, through active labor-market policies, affordable housing, and, where possible, remote work. Finally, adjustment takes time, and not every worker will be able to move immediately into a new occupation. Social protection and unemployment insurance therefore remain important, but, ideally, they should be combined with effective retraining and support for re-employment. Competition also matters: Skills should be able to move across enterprises rather than becoming concentrated in a few companies, which is why the report also emphasizes restrictions on non-compete agreements and appropriate scrutiny of mergers and acquisitions. The objective is not to stop technological change, but to make sure that more workers are able to move with it.

"In practice, technology can raise demand for highly skilled workers, while also increasing demand for lower-skilled service jobs, even as many routine middle-skill occupations come under pressure."

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<sup>9</sup> Find out more: <https://direct.mit.edu/rest/article-abstract/89/1/118/57634/Lousy-and-Lovely-Jobs-The-Rising-Polarization-of?redirectedFrom=fulltext>

<sup>10</sup> Find out more: <https://economics.mit.edu/sites/default/files/publications/Skills%2C%20Tasks%20and%20Technologies%20-%20Implications%20for%20.pdf>

<sup>11</sup> Find out more: <https://www.aeaweb.org/articles?id=10.1257/aer.103.5.1553>

"Brazil stands out as a country where potential demand is relatively strong compared with domestic supply. In fact, our estimates suggest that the share of recent graduates with the potential to supply new skills in Brazil is only about one-third of that in countries such as Ireland and Poland."

**I.S.O.\_** *The report also suggests that countries best positioned to benefit from the AI-driven economy combine investments in education, lifelong learning, and workforce reskilling. Beyond developing these skills, what else must emerging economies such as Brazil do to ensure that enterprises are able to absorb and make effective use of a more skilled workforce?*

**M.M.T.\_** Education and training are essential, but they are only one side of the equation. A country can produce workers with excellent new skills, but those skills will generate economic benefits only if enterprises are able—and have incentives—to use them. In other words, countries need both a supply of skills and enterprises that create demand for those skills.

This comes through clearly in our data. In the United States, the enterprises that are most likely to hire workers with new skills tend to be newer, more innovative, more productive, and less financially constrained. This suggests that the ability to absorb skills is closely connected to enterprises' capacity to innovate, invest, and grow. If enterprises cannot finance new technologies, experiment with new products, or expand into new markets, simply increasing the number of skilled workers may not be enough.

For Brazil, our Skill Imbalance Index<sup>12</sup> provides a particularly useful perspective. The index compares countries according to the balance between their potential demand for new skills and their capacity to supply them compared to the United States. Brazil stands out as a country where potential demand is relatively strong compared with domestic supply. In fact, our estimates suggest that the share of recent graduates with the potential to supply new skills in Brazil is only about one-third of that in countries such as Ireland and Poland. This means that, for Brazil, expanding training opportunities, strengthening Science, Technology, Engineering, and Mathematics (STEM) education, and integrating information technology (IT) skills more broadly across fields of study remain immediate priorities.

However, the other side should not be neglected. As Brazil expands the supply of skilled workers, enterprises also need to be able to absorb and deploy those skills. That means supporting the creation and growth of innovative enterprises, improving access to finance, reducing unnecessary barriers to starting and expanding businesses, and helping enterprises connect to international markets. These are the kinds of policies that can turn a more skilled workforce into higher productivity and better jobs.

So the broader lesson is that education and product-market reforms need to go hand in hand. Workers need the skills required by new technologies, but enterprises also need the financing, incentives, and competitive environment to adopt those technologies and put those skills to productive use.

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<sup>12</sup> Find out more: <https://www.imf.org/en/publications/staff-discussion-notes/issues/2026/01/09/bridging-skill-gaps-for-the-future-new-jobs-creation-in-the-ai-age-572136>

## Article II

# Skills for adaptability in the digital transformation<sup>13</sup>

*By International Labor Organization*

## Digital transformation and its impact on labor markets

The last few decades have witnessed rapid expansion in digital technologies, including Artificial Intelligence (AI), machine learning, robotics, autonomous systems (AS), and the Internet of Things (IoT). The extent to which countries, industries, and occupations are exposed to and adopt these technologies significantly influences their impacts on employment and skills. Greater exposure and adoption can drive job creation in technology-intensive sectors while transforming or even displacing jobs in others. Slower adoption, particularly in low- and middle-income countries, may limit opportunities but also shield these countries from potential negative impacts.

### **EXPOSURE TO DIGITAL TECHNOLOGIES**

To assess global exposure to emerging digital technologies across countries, various measures of exposure have been developed in the literature. These measures typically aim to capture the degree to which new technologies are relevant to specific industries or occupations. Some approaches rely on survey data containing detailed information on tasks (Arntz et al., 2016; Gmyrek et al., 2024), while others use patent data to identify how technologies are integrated into production processes or influence the tasks required for certain jobs (Dechezleprêtre et al., 2021; Mann & Püttmann, 2023; Prytkova et al., 2024). Importantly, the effects of digital technologies on employment outcomes depend on the level of exposure (and ultimate adoption), which varies across countries and income groups, as well as on complementary factors such as the workforce skills composition, organizational practices, institutions, and regulations that shape how these technologies translate into real impacts.

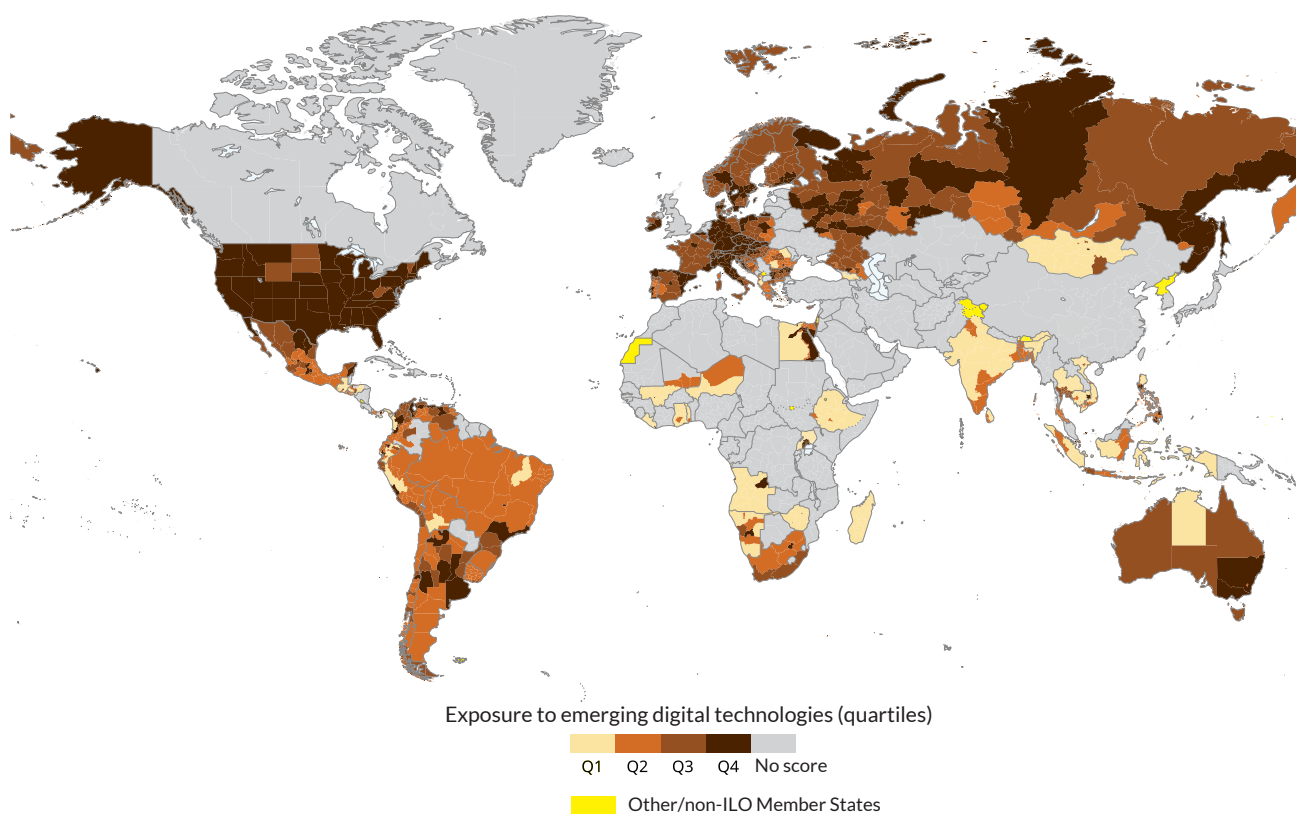
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To illustrate the cross-country variation in digital technology exposure, Figure 1 displays average exposure scores using the TechXposure measure (Prytkova et al., 2024). This measure captures exposure to 40 digital technologies<sup>14</sup> that have emerged over the past decade, based on natural language processing (NLP) methods—such as Sentence Transformers—applied to patent data. Exposure reflects the relevance of the 40 technologies to an industry, either through integration into production processes or by enhancing the industry’s output. These relevance scores were then correlated with employment shares by industry at the first subnational administrative level, using harmonized labor force and household surveys from the ILO Department of Statistics (ILOSTAT) for years close to 2010. This approach enables comparison of average exposure to emerging digital technologies across income groups and regions (Delaporte et al., in press). To facilitate comparison, subnational regions are grouped into quartiles based on their exposure, ranging from low to high exposure.

**Figure 1 - GLOBAL OVERALL EXPOSURE TO EMERGING DIGITAL TECHNOLOGIES AT THE FIRST SUBNATIONAL ADMINISTRATIVE LEVEL**



Disclaimer: Boundaries shown do not imply endorsement or acceptance by the ILO. See full disclaimer: [ilo.org/disclaimer](https://ilo.org/disclaimer)

Note: Data at the first subnational administrative level were available for 70 countries (9 low-income countries, 16 lower-middle-income countries, 19 upper-middle-income countries and 26 high-income countries).

Source: Delaporte et al. (in press).

<sup>14</sup> The 40 digital technologies are classified into nine families of emerging digital technologies, namely: (a) 3D printing, (b) embedded systems, (c) smart mobility, (d) food services, (e) e-commerce, (f) payment systems, (g) digital services, (h) computer vision, and (i) health technology. For details, please refer to Prytkova et al. (2024).

High-exposure regions (Q4) are concentrated in parts of North America (notably the United States and parts of Mexico), Europe (including much of Northern and Western Europe and parts of Eastern Europe), Australia, and some parts of South America (notably regions in Argentina and Chile). Several areas in Western Asia and parts of Southern Africa also register high exposure. This reflects the 2010 industry composition of these subnational regions, which tended to specialize in sectors more exposed to emerging digital technologies. Bangkok's employment was dominated by wholesale and retail trade alongside a sizable manufacturing base, while parts of the United States concentrated AI-intensive logistics and technology services. In contrast, lower-exposure areas (Q1 and Q2) are concentrated in sub-Saharan Africa, Southern and South-Eastern Asia, Central America, and parts of Eastern Europe. Many of these areas likely face constraints, such as limited digital infrastructure (Gmyrek et al., 2024), lower technological adoption rates, and lower investment in emerging technologies.

While examining the average exposure to digital technologies across countries is informative, it is important to distinguish between exposure and adoption of emerging digital technologies, as adoption levels may differ widely across countries. Importantly, exposure and adoption are positively correlated (Box 1). Even when adoption progresses more slowly than exposure, the growing diffusion and influence of digital technologies are already fundamentally changing the world of work, reshaping traditional job roles and altering the skills required to perform them.

Digitalization is also changing the structure of entire industries, from manufacturing and logistics to finance and health care. While there is general agreement that technological change has profound implications for employment, the scale and direction of these effects remain subjects of ongoing debate, as discussed next.

**Box 1 - EXPOSURE TO AND ADOPTION OF EMERGING DIGITAL TECHNOLOGIES ACROSS COUNTRIES**

Global exposure to digital technologies refers to the extent to which individuals, enterprises or economies are affected by digital innovations. It is typically measured through indicators like Internet penetration, digital infrastructure availability, and access to digital platforms. Exposure is therefore closely tied to the potential for adopting and utilizing digital technologies but does not guarantee their widespread use.

Global adoption of digital technologies refers to the actual integration of digital tools into economic activities, measured through metrics like business automation rates and information and communication technologies (ICT) usage in the workplace. Adoption depends on factors like skilled labor, infrastructure, and supportive policies.

A gap between exposure and adoption often exists, especially in low- and middle-income countries, where exposure may be high but adoption is limited due to lack of resources, sufficient infrastructure (Gmyrek et al., 2024), a skilled workforce, or regulatory support. By contrast, high-income countries generally see a smaller gap due to better access to these complementary assets.

Exposure and adoption of digital technologies are nevertheless often positively correlated. On average, as exposure increases, adoption increases proportionally (Saka et al., 2022). As expected, high-income countries tend to exhibit high exposure and high adoption, while lower-income countries display lower exposure and lower adoption rates.

Source: Prepared by the author.

## Skills as a driver of resilience

Digitalization is not only reshaping labor markets and altering the demand for skills but is also shaped by the skills available within the workforce. As jobs evolve and new tasks emerge, workers and enterprises must adapt their competencies accordingly. At the same time, equipping workers with the right mix of skills can influence how they and their regions experience digital change, either by unlocking new opportunities or by reducing the risk of exclusion. Identifying the specific skills that enable workers to navigate these changing conditions is therefore essential. This is especially important for helping displaced workers transition into emerging sectors and roles. Foundational skills, adaptability, and a commitment to lifelong learning have proven crucial in recent crises and remain essential to building resilient labor markets (Organisation for Economic Co-operation and Development [OECD] et al., 2024). Moreover, certain skill combinations can substantially improve employment outcomes.<sup>15</sup>

Table 1 - TAXONOMY OF SKILLS, THEIR DEFINITION, AND EXAMPLES OF KEYWORDS

| Subcategory                                      | Definition                                                                                                                                                                                                                                                                                            | Examples of keywords                                                                       |
|--------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|
| <b>Cognitive skills</b>                          |                                                                                                                                                                                                                                                                                                       |                                                                                            |
| Core cognitive skills                            | Skills needed to perform tasks that require analysis and calculation, problem-solving, intuition, and flexibility.                                                                                                                                                                                    | Planning, designing, problem- solving, strategic thinking, analysis, measuring, informing. |
| Sophisticated cognitive skills                   | Skills needed to perform more advanced tasks that require analysis, modeling, and creativity.                                                                                                                                                                                                         | Evaluation, research, statistics, data analysis.                                           |
| General computer skills                          | These six subcategories relate closely to the cognitive skills described above and correspond to skills that are needed in specific areas of work. They are listed as separate subcategories because they are often specifically mentioned in job advertisements and in applicants' work experiences. | Computer, Excel, Internet skills.                                                          |
| Software (specific) skills and technical support |                                                                                                                                                                                                                                                                                                       | Programming language, web development, computer repair.                                    |
| Machine learning and AI skills                   |                                                                                                                                                                                                                                                                                                       | Automation, neural networks, deep learning.                                                |
| Financial skills                                 |                                                                                                                                                                                                                                                                                                       | Budgeting, accounting, finance.                                                            |
| Writing skills                                   |                                                                                                                                                                                                                                                                                                       | Writing, editing, reports.                                                                 |
| Project and process management skills            |                                                                                                                                                                                                                                                                                                       | Project, process, product, and supply management.                                          |

CONTINUES ►

<sup>15</sup> See Chapter 3 of the original publication.

## ► CONCLUSION

| Subcategory                       | Definition                                                                                                                                                          | Examples of keywords                                              |
|-----------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|
| Socio-emotional skills            |                                                                                                                                                                     |                                                                   |
| Character skills                  | These skills are related to personal attributes, including conscientiousness, openness to experience, and emotional stability.                                      | Organized, energetic, time management, reliable.                  |
| Social skills                     | These skills encompass character traits associated with interpersonal interactions.                                                                                 | Communication, teamwork, empathy, advice, presentation.           |
| People management skills          | These two subcategories refer to specific abilities within the broader realm of social interactions that are frequently specified as prerequisites in job postings. | Supervision, leadership, mentoring, staff development.            |
| Customer service skills           |                                                                                                                                                                     | Client, patient, selling, buying, purchase.                       |
| Manual skills                     |                                                                                                                                                                     |                                                                   |
| Finger dexterity skills           | These skills are usually required in routine work, particularly in machine operation and the production or handling of goods.                                       | Picking, sorting, packing, using equipment, controlling machines. |
| Hand-foot-eye coordination skills | These “non-routine” skills are usually required for work in changing environments that necessitate adaptation.                                                      | Caring for animals, driving, renovations, repair, cleaning.       |
| Physical skills                   | This subcategory focuses on innate bodily characteristics.                                                                                                          | Resistance, carrying loads, physical strength, walking.           |

Note: This taxonomy is derived from a comprehensive review of economics and psychology literature. It builds on economic studies that exploit similar data, while also incorporating manual skills and broadening the conceptual basis of socioeconomic skills to enable analyses across labor markets.

Source: Adamczyk et al. (2025) and Escudero et al. (2024), who provide details on the underlying concepts and literature.

To assess how skills mediate the effects of digital exposure, the analysis examines how the impact of digital exposure varies depending on the baseline skill composition of occupations at the first subnational administrative level. Skill composition is calculated by combining the skill intensity of each occupation (that is, the relative importance of each skill within the occupation) with the occupational employment shares in each subnational unit. The skill intensity of occupations is derived from online job vacancy data in Brazil, the Russian Federation, South Africa, and Uruguay.<sup>16</sup>

<sup>16</sup> These skills measures are constructed using the comprehensive skills approach introduced in Chapter 3 of the original publication.

In lower-income countries, highly exposed areas which have a high share of jobs requiring cognitive skills tend to experience gains in employment among low- and middle-educated workers, while highly educated workers appear more vulnerable to displacement.

The analysis sheds new light on how certain skills mitigate the adverse effects, or amplify the positive impacts, of digital exposure on the employment-to-population ratio. The goal is to understand whether certain types of skills make subregions more resilient—or more vulnerable—to technological change.

The analysis (Table 2) finds that a number of cognitive skills play a key role in mediating the employment effects of digital exposure. Subregions characterized by a higher concentration of jobs requiring financial, computer, sophisticated cognitive, writing, and core cognitive skills (such as reasoning, problem-solving, and digital literacy) tend to experience better employment outcomes when exposed to digital technologies. Importantly, these effects remain even after controlling for the general educational composition of the workforce, suggesting that while education is a necessary foundation, it is the specific mix of skills that ultimately shapes outcomes. Similarly, subregions with greater demand for project and process management skills also tend to be better equipped to adapt to digital exposure, possibly because these skills foster the organizational flexibility and problem-solving needed to adjust workflows when technologies are introduced. These results reinforce the notion that advanced communication, organizational, and coordination skills are particularly valuable complements to technology.

Interestingly, while these positive mediating effects are observed across all country income levels, the effects are stronger in high-income countries. This may stem from more supportive institutional environments, including better access to digital infrastructure, training systems, and innovation ecosystems.

Importantly, the extent to which skills mediate the employment effects of digital exposure varies significantly depending on the education levels of workers within country income groups. Most cognitive skills are associated with positive employment outcomes—particularly for middle- and highly educated workers in high-income countries, and for highly educated workers in upper-middle-income contexts. This finding is in line with the idea that digital technologies tend to complement middle- and highly educated workers when local jobs require strong cognitive skills, because these workers are better positioned to adapt to task upgrading and to benefit from complementary technologies. In lower-income countries, highly exposed areas which have a high share of jobs requiring cognitive skills tend to experience gains in employment among low- and middle-educated workers, while highly educated workers appear more vulnerable to displacement. This pattern may reflect that digital exposure in these settings is still at an earlier stage, initially creating or transforming jobs that rely on basic or intermediate cognitive skills, rather than generating sufficient high-end roles.

However, not all cognitive skills are equally beneficial. Subregions with a high share of jobs requiring machine learning and AI or software/technical skills appear to fare worse in terms of employment growth following digital exposure. These more specialized digital skills also follow a different pattern with regard to the educational groups affected. In high-income countries, these skills are associated with positive employment effects for middle- and highly educated workers, where these skills are complements to production technologies and organizational processes that are already digitally mature. In contrast, in lower-income settings, where these technologies are still emerging, these skills are associated with job displacement among both low- and highly educated workers, while those with middle education levels experience employment gains, reflecting a polarization mechanism with limited high-skill absorption.

These patterns may indicate a misalignment between the increased demand for advanced digital skills and the preparedness of the workforce, who may lack the specific competencies required, although the analysis does not directly test for such mismatches. They may also reflect the fact that the data predate the rapid spread of generative AI, which tends to reshape tasks within jobs rather than fully displace employment. In either case, the findings highlight the importance of context-sensitive digital skill strategies that align with local labor market structures and evolving technological realities.

**Table 2 - THE MEDIATING ROLE OF SKILLS BY COUNTRY INCOME GROUP AND EDUCATION LEVEL (PERCENTAGE POINTS)<sup>17</sup>**

|                                           | All   |     | Low education level |     | Middle education level |     | High education level |     |
|-------------------------------------------|-------|-----|---------------------|-----|------------------------|-----|----------------------|-----|
| Low- and lower-middle-income              |       |     |                     |     |                        |     |                      |     |
| Exposure x                                |       |     |                     |     |                        |     |                      |     |
| Core cognitive                            | 0.28  | *** | 0.40                | *** | 0.10                   | *** | -0.05                | *** |
| Sophisticated cognitive                   | 1.39  | *** | 1.26                | *** | 0.91                   | *** | -0.41                | *** |
| General computer                          | 0.84  | *** | 1.27                | *** | 0.38                   | *** | -0.61                | *** |
| Software (specific) and technical support | 0.12  |     | -0.47               | *** | 1.43                   | *** | -0.71                | *** |
| Machine learning and AI                   | -3.73 | *** | -10.37              | *** | 8.41                   | *** | -2.25                | *** |
| Financial                                 | 1.64  | *** | 2.40                | *** | 0.32                   | *** | -0.60                | *** |
| Writing                                   | 2.68  | *** | 3.03                | *** | 0.73                   | *** | -0.80                | *** |
| Project and process management            | 5.55  | *** | 6.92                | *** | 1.93                   | *** | -1.93                | *** |
| Character                                 | -0.15 | **  | 0.06                |     | -0.32                  | *** | 0.10                 | *** |
| Social                                    | -0.25 | *** | -0.22               | *** | -0.07                  | *** | -0.04                | *** |
| People management                         | 1.45  | *** | 2.08                | *** | 0.06                   | *** | -0.42                | *** |
| Customer service                          | -0.36 | *** | -0.31               | *** | -0.06                  | *** | -0.06                | *** |
| Finger dexterity                          | 0.11  | *** | -0.06               |     | -0.12                  | *** | 0.25                 | *** |
| Hand-foot-eye coordination                | -0.61 | *** | -0.89               | *** | -0.17                  | *** | 0.33                 | *** |
| Physical                                  | -0.65 | *** | -0.80               | *** | -0.33                  | *** | 0.42                 | *** |

CONTINUES ►

<sup>17</sup> This table presents the estimates for the interaction between digital exposure and measures of the subnational skill composition in 2010. It presents the coefficients measuring the mediating effect of the subnational skill composition on changes in the employment-to-population ratio over the period 2014 to 2019. Each coefficient comes from a separate regression. Control variables include country-fixed effects and demographic characteristics from 2010, including the logarithm of the working-age population, share of females, and proportion of the population 55 years old or older. The sum of exposure shares is also included as a covariate. Lastly, measures of the supply side of skilled labor in 2010 are included, namely, the share of low-, middle- and highly educated workers. For the list of countries included in the analysis, see Delaporte et al. (in press).

## /Internet Sectoral Overview

► CONTINUES

|                                           | All    |     | Low education level |     | Middle education level |     | High education level |     |
|-------------------------------------------|--------|-----|---------------------|-----|------------------------|-----|----------------------|-----|
| Exposure x                                |        |     |                     |     |                        |     |                      |     |
| Core cognitive                            | 0.16   | *** | -0.08               | **  | -0.20                  | *** | 0.28                 | *** |
| Sophisticated cognitive                   | 0.39   | **  | -1.12               | *** | 0.22                   | *** | 1.06                 | *** |
| General computer                          | 0.78   | *** | -0.20               | *** | -0.53                  | *** | 1.38                 | *** |
| Software (specific) and technical support | -2.25  | *** | -2.04               | *** | 2.08                   | *** | -2.57                | *** |
| Machine learning and AI                   | -12.79 | *** | -15.70              | *** | 12.66                  | *** | -11.41               | *** |
| Financial                                 | 0.65   | *** | -0.63               | *** | -0.57                  | *** | 1.57                 | *** |
| Writing                                   | 1.68   | *** | -1.26               | *** | -0.79                  | *** | 3.15                 | *** |
| Project and process management            | 0.85   |     | -2.26               | *** | 0.78                   | *** | 2.80                 | *** |
| Character                                 | -0.02  |     | 0.42                | *** | 0.22                   | *** | -0.68                | *** |
| Social                                    | 0.05   | *   | -0.17               | *** | 0.08                   | *** | 0.15                 | *** |
| People management                         | -0.18  | *   | -0.66               | *** | -0.46                  | *** | 0.75                 | *** |
| Customer service                          | -0.17  | *** | -0.16               | *** | 0.11                   | *** | -0.12                | *** |
| Finger dexterity                          | 0.21   | **  | 0.27                | *** | -0.21                  | *** | 0.11                 | *** |
| Hand-foot-eye coordination                | 0.03   |     | 0.33                | *** | 0.08                   | *** | -0.32                | *** |
| Physical                                  | 0.11   |     | 0.83                | *** | -0.26                  | *** | -0.47                | *** |
| High-income                               |        |     |                     |     |                        |     |                      |     |
| Exposure x                                |        |     |                     |     |                        |     |                      |     |
| Core cognitive                            | 1.94   | *** | -1.76               | *** | -3.42                  | *** | 2.58                 | *** |
| Sophisticated cognitive                   | 0.59   | *   | -1.63               | *** | 3.25                   | *** | 1.69                 | *** |
| General computer                          | 1.21   | *** | -1.22               | *** | 2.73                   | *** | 2.64                 | *** |
| Software (specific) and technical support | -1.37  | *** | -2.67               | *** | 2.65                   | *** | 1.36                 | *** |
| Machine learning and AI                   | -12.08 | *** | -29.45              | *** | 14.14                  | *** | 26.53                | *** |
| Financial                                 | 2.44   | *** | -2.91               | *** | 3.75                   | *** | 3.52                 | *** |
| Writing                                   | 9.15   | *** | 0.67                |     | -12.37                 | *** | 14.67                | *** |
| Project and process management            | 0.77   |     | -9.95               | *** | 11.74                  | *** | 19.49                | *** |
| Character                                 | 1.89   | *** | 2.96                | *** | -0.36                  | *** | -5.13                | *** |

## ► CONCLUSION

|                            | All   |     | Low education level |     | Middle education level |     | High education level |     |
|----------------------------|-------|-----|---------------------|-----|------------------------|-----|----------------------|-----|
| Social                     | -0.96 | *** | 0.94                | *** | 3.23                   | *** | -0.98                | *** |
| People management          | 2.84  | *** | -1.27               | *** | -2.34                  | *** | 3.98                 | *** |
| Customer service           | -0.86 | *** | -0.31               | *** | 1.59                   | *** | 0.17                 | *** |
| Finger dexterity           | 0.42  | *** | 1.16                | *** | -0.72                  | *** | -1.73                | *** |
| Hand-foot-eye coordination | 0.02  |     | 0.76                | *** | -1.56                  | *** | -0.89                | *** |
| Physical                   | 0.68  | **  | 3.35                | *** | -2.55                  | *** | -4.90                | *** |

■ 21 to 30 ■ 16 to 20.9 ■ 11 to 15.9 ■ 6 to 10.9 ■ 1 to 5.9  
□ -0.9 to 0.9 ■ -5.9 to -1 ■ -10.9 to -6 ■ -15.9 to -11 ■ -30 to -16

Key: \* = significant at the 10 percent level; \*\* = significant at the 5 percent level; \*\*\* = significant at the 1 percent level.

Source: Delaporte et al. (in press).

The mediating effects of socio-emotional skills are generally smaller with less clear patterns among country income groups. People management stands out as a positive mediator in both low- and high-income countries, suggesting that roles involving team coordination and supervisory responsibilities complement technological change.

In contrast, customer service and social skills are associated with weaker employment outcomes in both low- and high-income countries. However, when differentiating by educational levels of the workforce, most of these skills exhibit a positive mediating effect for middle-educated workers in high-income countries, likely reflecting the complementarity of these interpersonal skills with technology and their potential to be augmented rather than replaced by it in increasingly service-oriented roles.

Finally, the effects of manual skills are not uniform across contexts. In upper-middle- and high-income countries, manual skills are associated with employment gains for low-educated workers, but negative effects for middle- and highly educated workers. This pattern suggests a mismatch between qualification levels and task demands: While demand persists for certain manual, non-automatable tasks typically performed by low-educated workers, middle- and highly educated workers with manual skill profiles may be suffering from displacement.

By contrast, in low- and lower-middle-income countries, manual skills are associated with negative employment effects for low- and middle-educated workers, while highly educated workers tend to benefit. This pattern likely reflects structural differences in task content and technological adoption: Among less-educated workers, manual skills are often concentrated in routine, physically intensive jobs that are more vulnerable to automation, offshoring, or informality. Meanwhile, highly educated workers with manual competencies are more likely employed in specialized, precision-oriented or technology-complementary tasks—for example, advanced manufacturing, medical technology or maintenance of sophisticated equipment—where manual dexterity and technical knowledge complement digital tools rather than compete with them.

Ensuring an inclusive digital transition will depend not only on increasing access to technology and improving digital skills, but also on building the right mix of skills that enable all workers—especially the most vulnerable—to benefit from these transformations.

Overall, the analysis underscores that the employment impacts of exposure to digital technologies are not uniform but are strongly mediated by the underlying skill composition of the workforce. Not all skills offer the same protection against digital exposure. While several cognitive and socio-emotional skills—particularly financial literacy, computer use, core reasoning abilities, and people management—play a pivotal role in enabling subregions to translate digital exposure into employment gains, the effects vary significantly by country income level, educational attainment, and type of skill.

However, more specialized digital skills—such as machine learning and AI, and software competencies—present a double-edged sword. In high-income countries, they are associated with positive effects for highly educated workers to the detriment of low-educated workers, while in lower-income countries, these skills are linked to displacement among both low- and highly educated workers. This highlights how uneven digital readiness across contexts and the level of preparedness of the local labor force can shape whether advanced skills lead to opportunity or exclusion.

These results highlight the importance of moving beyond general education policies to develop targeted, context-sensitive skill policies that respond to the pace and nature of digital exposure. Ensuring an inclusive digital transition will depend not only on increasing access to technology and improving digital skills, but also on building the right mix of skills that enable all workers—especially the most vulnerable—to benefit from these transformations.

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## Interview II

### Digital transformation and the future of work in industry

In this interview, Wilson Cardoso, technical advisor at the National Service for Industrial Training – São Paulo Regional (Senai-SP), discusses the challenges of digital transformation in Brazilian industry, highlighting the demands for professional qualification and the main barriers to the adoption of digital technologies and Artificial Intelligence (AI). He also discusses the role of Senai-SP in the training and retraining of workers, as well as in supporting enterprises in their innovation and digital transformation processes.

**Internet Sectoral Overview (I.S.O.)\_ The ICT Enterprises survey<sup>18</sup> indicates that the use of digital technologies and, more recently, AI tools has grown among Brazilian enterprises. However, this adoption still varies significantly according to the enterprise size and activity sector. What are the main obstacles today to expanding the adoption of these technologies by Brazilian industry?**

**Wilson Cardoso (W.C.)\_** The increased adoption of digital technologies and AI by Brazilian industry faces challenges that go beyond the acquisition of tools or infrastructure. One of the main obstacles is the shortage of qualified professionals to design, implement, and operate advanced solutions in automation, data analysis, AI, cloud computing, and cybersecurity. Although the supply of technologies is growing rapidly, many enterprises still find it difficult to form multidisciplinary teams capable of transforming data into concrete gains in productivity, quality, and competitiveness. Another important factor is the coexistence of legacy systems with new digital platforms. Much of the Brazilian industrial base was built over decades and has equipment, software, and processes developed in different technological periods. The integration of these environments with modern AI solutions, the Industrial Internet of Things (IIoT), manufacturing execution systems (MES), enterprise resource planning (ERP), and smart manufacturing platforms requires investment, specialized knowledge, and long-term planning.

Economic constraints also play a significant role, especially for micro, small, and medium enterprises (MSME). Many organizations still perceive digital transformation as being high in cost with uncertain or long-term financial returns. In many cases, organizations lack the resources to conduct pilot projects, proof-of-concept studies, and feasibility assessments that demonstrate the concrete benefits of digitalization.

Furthermore, data quality and availability remain a challenge. AI systems depend on reliable, structured, and accessible data. However, many enterprises still operate with scattered information, departmental silos, and predominantly manual processes, hindering the construction of robust analytical models.



**Wilson Cardoso**  
Technical advisor  
at Senai-SP

Photo: SENAI - Technology Advisory Services

<sup>18</sup> Data from the ICT Enterprises 2025 survey, by the Regional Center for Studies on the Development of the Information Society (Cetic.br), a sector of the Brazilian Network Information Center (NIC.br), available at: <https://cetic.br/en/pesquisa/empresas/>

“The evolution of Industry 4.0 and advances in concepts such as generative AI, edge computing, digital twins, 5G private networks, and smart manufacturing demand professionals who can work in increasingly connected, data-driven environments.”

Issues related to cybersecurity and data protection also impact adoption. As factories, machines, and processes become more connected, concerns about cyberattacks, operational disruptions, and regulatory compliance grow.

Finally, there is a cultural and strategic issue. Many enterprises are in the early stages of digital maturity and find it difficult to define priorities, establish return metrics, and align digital transformation with business objectives. In this context, initiatives for professional development, technology demonstration, applied research, and technology transfer, such as those developed by Senai-SP in partnership with industry, are fundamental to reducing barriers, accelerating the adoption of AI, and strengthening the competitiveness of Brazilian industry on the global stage.

***I.S.O.\_ As digital transformation advances, which digital skills become more strategic for Brazilian industry? How does Senai-SP identify the main professional qualification gaps in this context?***

***W.C.\_*** As digital transformation progresses, skills related to data analytics, AI, industrial automation, cybersecurity, cloud computing, the Internet of Things (IoT), systems integration, and software development are becoming increasingly strategic for Brazilian industry. Equally important is the development of transversal skills such as analytical thinking, complex problem-solving, collaborative work, adaptability to change, and continuous learning.

The evolution of Industry 4.0 and advances in concepts such as generative AI, edge computing, digital twins, 5G private networks, and smart manufacturing demand professionals who can work in increasingly connected, data-driven environments. The challenge lies not only in applying the tools but also in the ability to use them to improve production processes, optimize resources, increase productivity, and support evidence-based decision-making.

At Senai-SP, we identify professional qualification gaps through a combination of methodologies that connect education, technology, and the real demands of the productive sector. One of the main instruments is the Industrial Employment Map<sup>19</sup>, a study that monitors technological trends, occupational transformations, and future workforce needs in industry. This analysis makes it possible to identify which professions are growing, which skills are becoming critical, and where the greatest skills gaps are.

Beyond the Industrial Employment Map, Senai-SP maintains ongoing relationships with enterprises, industrial unions, sectoral associations, research centers, and innovation ecosystems. This proximity enables real-time monitoring of technological changes across industrial segments, allowing continuous adjustment of curricula for technical courses, qualification programs, and undergraduate, postgraduate, and corporate education.

The Senai-SP Technological Network plays a fundamental role in this process. By developing applied research projects, proof-of-concept studies, and technology transfer in partnership with enterprises, the network can identify emerging skills even before their widespread dissemination in the market.

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<sup>19</sup> Find out more: <https://www.portaldaindustria.com.br/canaais/observatorio-nacional-da-industria/produtos/mapa-do-trabalho-industrial-2025-2027/> (available in Portuguese)

In this way, Senai-SP not only trains professionals for current demands but also anticipates the skills needed for the coming years, contributing to ensuring that São Paulo and Brazilian industries have the talent capable of leading their digital transformation and increasing their competitiveness in an increasingly technological global landscape.

***I.S.O.\_ How are technological changes transforming professional profiles and the demands of the industrial labor market? What initiatives has Senai-SP developed to prepare and retrain workers in this new scenario of digital transformation?***

**W.C.\_** Technological changes are profoundly transforming the professional profiles of the industry. While many roles were previously predominantly operational, today there is a growing demand for professionals capable of interacting with digital systems, interpreting data, operating advanced technologies, and working in increasingly automated and connected environments. The trend, therefore, is not the replacement of workers by technology, but the transformation of activities and the skills needed to perform work more efficiently and innovatively.

Technologies such as AI, IoT, advanced robotics, smart manufacturing, cloud computing, 5G private networks, computer vision, and digital twins are redefining production processes and demanding professionals with more comprehensive and multidisciplinary technical training. In this new scenario, digital knowledge is being combined with traditional skills in engineering, automation, maintenance, production, and industrial management.

In addition to technical skills, socio-emotional skills are increasing in importance. The capacity for continuous learning, critical thinking, complex problem-solving, creativity, collaboration, and adaptability has become an important differentiator for professionals who need to keep up with rapid technological evolution.

To meet this challenge, Senai-SP has been working on multiple fronts in professional qualification and requalification. Based on trends identified by the Industrial Employment Map and ongoing dialogue with enterprises and productive sectors, the institution continuously updates its curricula and educational programs, incorporating new digital skills into technical courses, professional qualification, and undergraduate, postgraduate, and executive education.

Senai-SP also invests in advanced laboratories, practical learning environments, and programs focused on enabling technologies for Industry 4.0, so that students develop skills aligned with the real needs of industry. In parallel, the Senai Institutes of Innovation and Technology promote applied research and technology transfer projects that expose students, teachers, and professionals to the challenges faced by enterprises.

Another important aspect is offering refresher and requalification programs for workers already in the market. These programs help professionals keep up with technological evolution without needing a complete career change, strengthening their employability and supporting the competitiveness of enterprises.

"In addition to technical skills, socio-emotional skills are increasing in importance. The capacity for continuous learning, critical thinking, complex problem-solving, creativity, collaboration, and adaptability has become an important differentiator for professionals who need to keep up with rapid technological evolution."

"A common trend across all sectors is the growing use of data as a strategic asset. In this context, Senai-SP develops solutions that integrate information from machines, production processes, logistics, and business management, creating digital environments capable of supporting faster and more accurate decisions."

**I.S.O.\_** *In addition to training and professional development, Senai-SP also supports enterprises in their digital transformation processes. What demands appear most frequently, and what solutions has Senai-SP developed to meet them?*

**W.C.\_** Digital transformation has become essential for the competitiveness of industry, and Senai-SP supports enterprises in virtually all economic sectors in the state of São Paulo. This includes highly diverse sectors: agribusiness, food and beverages, paper and pulp, chemicals, oil and gas, energy, mining, metalworking, automotive, machinery and equipment, construction, health care, pharmaceuticals, electronics, telecommunications, logistics, defense, and aerospace.

Despite the specific characteristics of each sector, some demands are recurring, including the digitalization of production processes, integration between industrial and corporate systems, use of data for decision-making, advanced automation, application of AI, IIoT, traceability, energy efficiency, predictive maintenance, and strengthening cybersecurity.

To meet these needs by operating through its network of schools—Senai Institutes of Technology and Senai Institutes of Innovation—Senai-SP offers everything from digital maturity diagnostics to complete research, development, and innovation projects. Support includes technological assessment, development of proof-of-concept projects, implementation of pilot solutions, technology transfer, and training of the teams involved.

In agribusiness, projects related to precision agriculture, connectivity, remote monitoring, and optimization of input use are frequent. In manufacturing, applications of computer vision, robotics, intelligent automation, real-time monitoring, and integration between the factory floor and corporate systems stand out. In the energy and infrastructure sectors, the adoption of technologies for asset management, operational efficiency, and predictive maintenance is growing. In high-tech segments such as defense, microelectronics, telecommunications, and aerospace, the demands for AI, embedded systems, advanced connectivity, digital twins, and advanced manufacturing are increasing.

A common trend across all sectors is the growing use of data as a strategic asset. In this context, Senai-SP develops solutions that integrate information from machines, production processes, logistics, and business management, creating digital environments capable of supporting faster and more accurate decisions. Beyond technological implementation, Senai-SP's distinguishing feature lies in the combination of innovation, technology, and people development. In this way, enterprises not only adopt new digital solutions but also develop the necessary skills to operate, evolve, and capture value from these technologies, accelerating their digital transformation journey and strengthening the competitiveness of São Paulo and Brazilian industry.

# Domain Report

## Domain registration dynamics in Brazil and around the world

The Regional Center for Studies on the Development of the Information Society (Cetic.br), department of the Brazilian Network Information Center (NIC.br), carries out monthly monitoring of the number of country code top-level domains (ccTLD) registered in countries that are part of the Organisation for Economic Co-operation and Development (OECD) and the G20.<sup>20</sup> Considering members from both blocs, the 20 nations with the highest activity sum more than 99.55 million registrations. In August 2026, domains registered under .de (Germany) reached 18.98 million, followed by China (.cn), United Kingdom (.uk), and Netherlands (.nl), with 11.98 million, 9.08 million, and 6.18 million registrations, respectively. Brazil had 5.91 million registrations under .br, occupying 6th place on the list (Table 1).<sup>21</sup>

From a global perspective, ccTLD account for a significant share of the domain name market. According to Verisign's *Domain Name Industry Brief*<sup>22</sup>, at the end of the second quarter of 2026, there were 401.6 million domain name registrations across all Top-Level Domains (TLD), including ccTLD and generic Top-Level Domains (gTLD), representing an increase of 8.1% compared with the same period in 2025. Of this total, 148.6 million registrations corresponded to ccTLD, a segment that grew by 3.6% year over year and 1.6% compared with the previous quarter. In this context, the number of registrations under .br places Brazil among the countries with the largest presence in the global ecosystem of country-code and territory-code domains.

The size of domain registration bases, however, should be analyzed considering the characteristics of national Internet ecosystems and the different management models adopted by ccTLD registries. There is considerable diversity in terms of scale, registration rules, and market presence, reflecting not only the size of each country's population or economy, but also factors such as registration policies and requirements, security practices and service quality, pricing, the development of e-commerce and digital services, and the extent to which the national domain is used by businesses, organizations, and individuals. Thus, comparisons among ccTLDs should be interpreted not merely as a measure of the size of their respective registration bases, but also in light of the different characteristics and trajectories of national digital ecosystems.

<sup>20</sup> Group composed by the 19 largest economies in the world and the European Union. More information available at: <https://g20.org/>

<sup>21</sup> The table presents the number of ccTLD domains according to the indicated sources. The figures correspond to the record published by each country, considering members from the OECD and G20. For countries that do not provide official statistics supplied by the domain name registration authority, the figures were obtained from: <https://research.domaintools.com/statistics/tld-counts>. It is important to note that there are variations among the date of reference, although the most up-to-date data for each country is compiled. The comparative analysis for domain name performance should also consider the different management models for ccTLD registration. In addition, when observing rankings, it is important to consider the diversity of existing business models.

<sup>22</sup> Find out more: <https://www.verisign.com/news-insights/domain-name-industry-brief/>

## /Internet Sectoral Overview

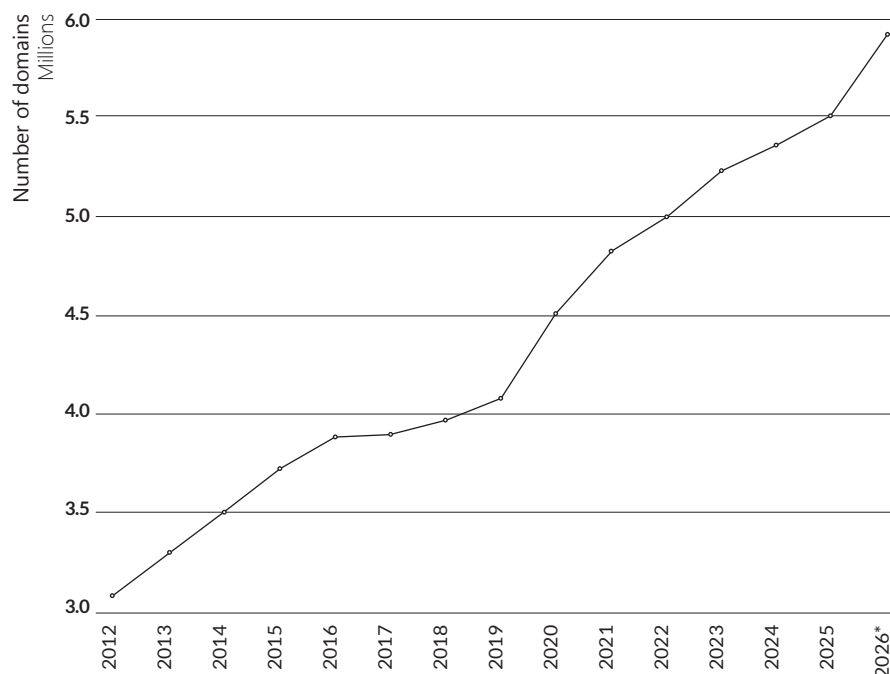
Table 1 – TOTAL REGISTRATION OF DOMAIN NAMES AMONG OECD AND G20 COUNTRIES

| Position | Country              | Number of domains | Date of reference | Source (website)                                                                                                                          |
|----------|----------------------|-------------------|-------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| 1        | Germany (.de)        | 18,148,184        | 01/09/2026        | <a href="https://www.denic.de">https://www.denic.de</a>                                                                                   |
| 2        | China (.cn)          | 11,981,364        | 01/09/2026        | <a href="https://research.domaintools.com/statistics/tld-counts/">https://research.domaintools.com/statistics/tld-counts/</a>             |
| 3        | United Kingdom (.uk) | 9,086,513         | 31/07/2026        | <a href="https://nominet.uk/reports-and-statistics/">https://nominet.uk/reports-and-statistics/</a>                                       |
| 4        | Netherlands (.nl)    | 6,187,762         | 31/08/2026        | <a href="https://stats.sidnlabs.nl/en/registration.html">https://stats.sidnlabs.nl/en/registration.html</a>                               |
| 5        | Russia (.ru)         | 6,184,806         | 01/09/2026        | <a href="https://cctld.ru">https://cctld.ru</a>                                                                                           |
| 6        | <b>Brazil (.br)</b>  | <b>5,915,979</b>  | <b>31/08/2026</b> | <b><a href="https://registro.br/dominio/estatisticas/">https://registro.br/dominio/estatisticas/</a></b>                                  |
| 7        | France (.fr)         | 4,568,249         | 31/08/2026        | <a href="https://www.afnic.fr/en/observatory-and-resources/statistics/">https://www.afnic.fr/en/observatory-and-resources/statistics/</a> |
| 8        | Australia (.au)      | 4,417,830         | 01/09/2026        | <a href="https://www.auda.org.au/">https://www.auda.org.au/</a>                                                                           |
| 9        | European Union (.eu) | 3,654,861         | 01/09/2026        | <a href="https://research.domaintools.com/statistics/tld-counts/">https://research.domaintools.com/statistics/tld-counts/</a>             |
| 10       | Canada (.ca)         | 3,633,865         | 01/09/2026        | <a href="https://www.cira.ca">https://www.cira.ca</a>                                                                                     |
| 11       | Italy (.it)          | 3,624,531         | 01/09/2026        | <a href="http://nic.it">http://nic.it</a>                                                                                                 |
| 12       | India (.in)          | 3,517,769         | 01/09/2026        | <a href="https://research.domaintools.com/statistics/tld-counts/">https://research.domaintools.com/statistics/tld-counts/</a>             |
| 13       | Colombia (.co)       | 3,212,200         | 01/09/2026        | <a href="https://research.domaintools.com/statistics/tld-counts/">https://research.domaintools.com/statistics/tld-counts/</a>             |
| 14       | Poland (.pl)         | 2,647,457         | 01/09/2026        | <a href="https://research.domaintools.com/statistics/tld-counts/">https://research.domaintools.com/statistics/tld-counts/</a>             |
| 15       | Switzerland (.ch)    | 2,647,307         | 15/08/2026        | <a href="https://www.nic.ch/statistics/domains/">https://www.nic.ch/statistics/domains/</a>                                               |
| 16       | Spain (.es)          | 2,447,193         | 31/07/2026        | <a href="https://www.dominios.es/es/sobre-dominios/estadisticas">https://www.dominios.es/es/sobre-dominios/estadisticas</a>               |
| 17       | Portugal (.pt)       | 2,179,334         | 01/09/2026        | <a href="https://www.dns.pt/en/statistics/">https://www.dns.pt/en/statistics/</a>                                                         |
| 18       | United States (.us)  | 1,899,773         | 31/05/2026        | <a href="https://www.about.us/stats-trends">https://www.about.us/stats-trends</a>                                                         |
| 19       | Japan (.jp)          | 1,890,104         | 01/09/2026        | <a href="https://jprs.co.jp/en/stat/">https://jprs.co.jp/en/stat/</a>                                                                     |
| 20       | Belgium (.be)        | 1,708,050         | 01/09/2026        | <a href="https://www.dnsbelgium.be/en">https://www.dnsbelgium.be/en</a>                                                                   |

Collection date: September 1, 2026.

Chart 1 shows the performance of .br since 2012.

**Chart 1 – TOTAL NUMBER OF DOMAIN REGISTRATIONS FOR .BR – 2012 to 2026\***



\*Collection date: August 31, 2026.

Source: Registro.br

Retrieved from: <https://registro.br/dominio/estatisticas>

In August 2026, the five generic gTLD totaled more than 206.45 million registrations. With 166 million registrations, .com ranked first, as shown in Table 2.

**Table 2 – TOTAL NUMBER OF DOMAINS AMONG MAIN gTLD**

| Position | gTLD | Number of domains |
|----------|------|-------------------|
| 1        | .com | 166.003.417       |
| 2        | .net | 12.386.155        |
| 3        | .org | 12.118.493        |
| 4        | .xyz | 9.657.010         |
| 5        | .top | 6.286.670         |

Collection date: September 1, 2026.

Source: DomainTools.com

Retrieved from: [research.domaintools.com/statistics/tld-counts](https://research.domaintools.com/statistics/tld-counts)

# Internet markers in Brazil

IX.br is an initiative of NIC.br, supported by CGI.br, that promotes direct interconnection among the networks that make up the Internet in Brazil. Through IXP, it makes traffic more direct and efficient, improving Internet quality, reducing costs, and increasing network resilience.

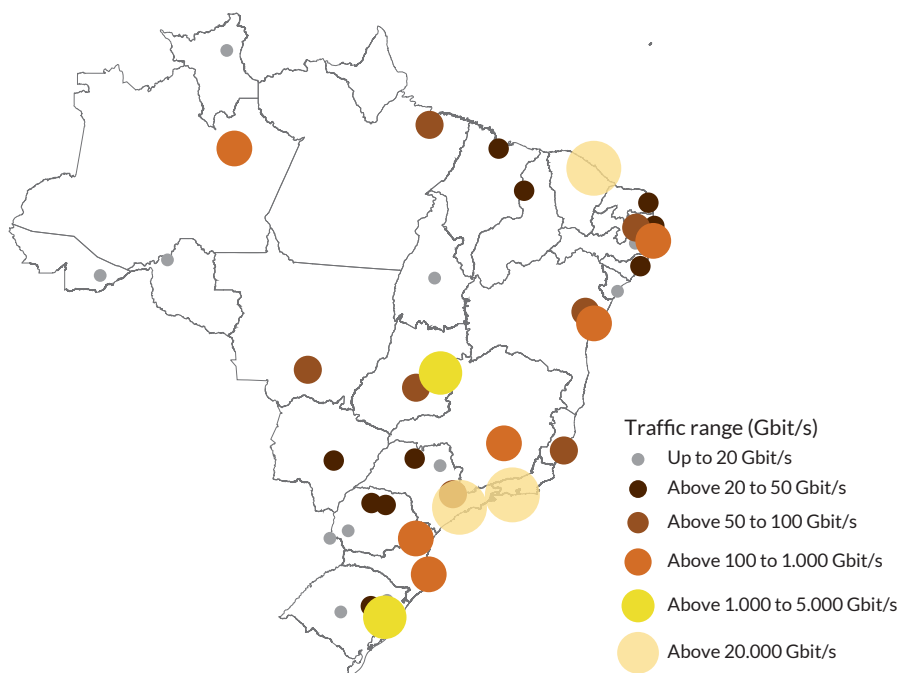
## IX.br: Data on Internet Exchange Points

O IX.br<sup>23</sup> (Brazil Internet Exchange) is an initiative of the Brazilian Network Information Center (NIC.br), supported by the Brazilian Internet Steering Committee (CGI.br), which promotes and implements Internet Exchange Points (IXP), the necessary infrastructure for direct interconnection between the networks, also known as Autonomous Systems (AS), which make up the Internet in Brazil.

The interconnection of several AS in an IXP simplifies Internet transit, establishing more direct traffic to a given destination. This improves quality, reduces costs, and increases network resilience.

The initiative currently encompasses 38 independent IXP, distributed throughout Brazil (Figure 1), and is one of the most important clusters of IXP worldwide. Chart 1 shows the continuous traffic growth of the IXP cluster that comprises IX.br over the past five years.

Figure 1 – IXP IN BRAZIL, BY TRAFFIC RANGE

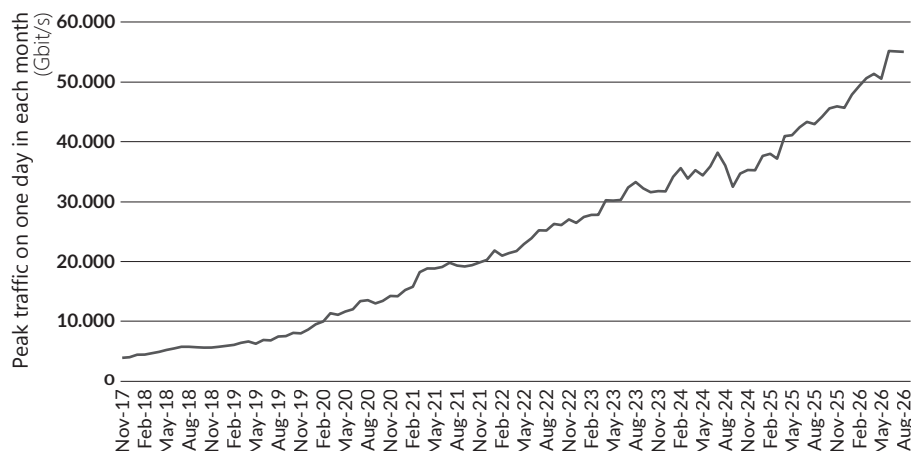


Reference period: August 2026.

Source: IX.br | NIC.br

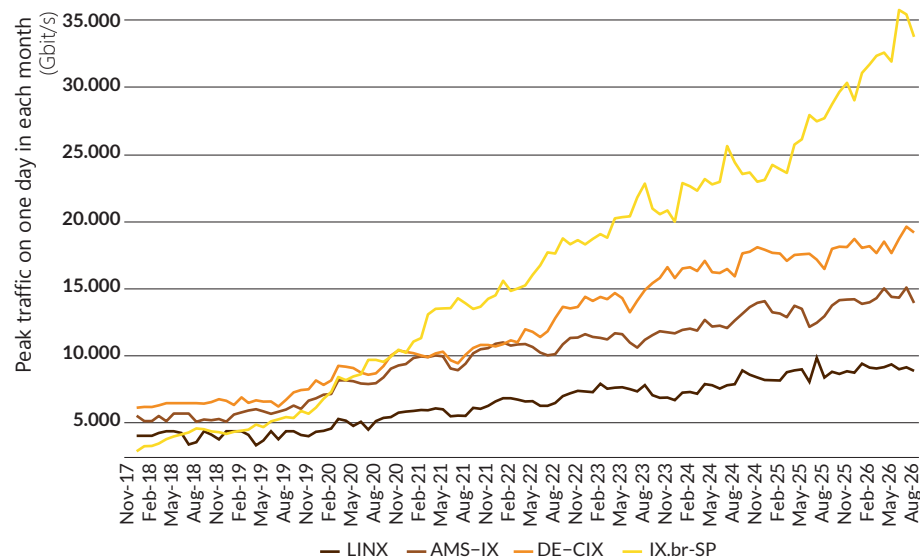
Retrieved from: <https://ix.br/trafego/agregado/>

<sup>23</sup> Find out more: <https://ix.br/>

**Chart 1 – TRAFFIC PEAK FOR THE IX.br INTERNET EXCHANGE POINT CLUSTER – 2017 to 2026**

Source: IX.br | NIC.br  
Retrieved from: <https://ix.br/agregado/>

Chart 2 compares the peak traffic of the São Paulo IXP, the largest in Brazil, with the three largest in Europe: LINX (London, England), AMS-IX (Amsterdam, Netherlands), and DE-CIX (Frankfurt, Germany), between 2017 and 2026.

**Chart 2 – LONDON (LINX), AMSTERDAM (AMS-IX), FRANKFURT (DE-CIX) AND SÃO PAULO (IX.br-SP) IXP, BY TRAFFIC PEAK - 2017 to 2026**

Source: IX.br | NIC.br  
Retrieved from: <https://www.de-cix.net/en/locations/frankfurt/statistics>; <https://www.ams-ix.net/ams/documentation/total-stats>; <https://portal.linx.net/services/lans-snmip>; <https://ix.br/trafego/agregado/>

Currently, IX.br has 39 independent IXP distributed throughout Brazil and is among the largest collections of IXP in the world. Since 2021, the São Paulo IXP has surpassed the largest European IXP in traffic volume, recording nearly twice the traffic of the largest of them (Chart 2).



Here you can find more information about IX.br's activities and statistics.

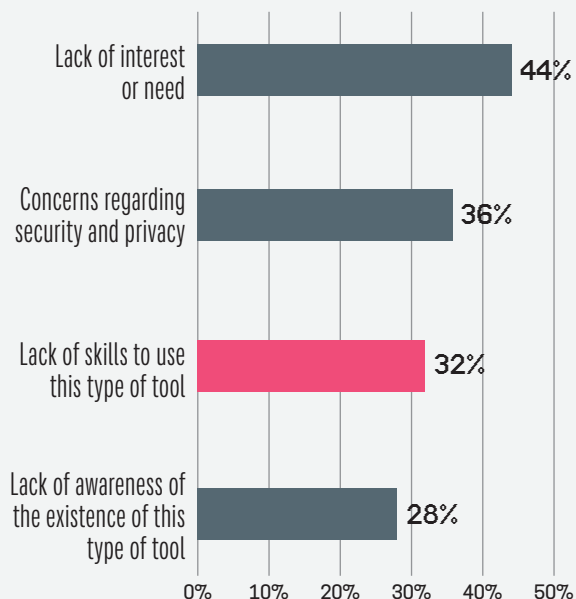
# Barriers to AI use in the Brazilian labor market

Artificial Intelligence (AI) has been adopted in some segments of the Brazilian labor market. Among the population, 26.2 million people report using AI tools for professional activities,<sup>24</sup> while in the business sector, half of large enterprises (those with 250 or more employed persons) report using this technology.<sup>25</sup> Despite this progress, significant barriers to AI adoption remain.

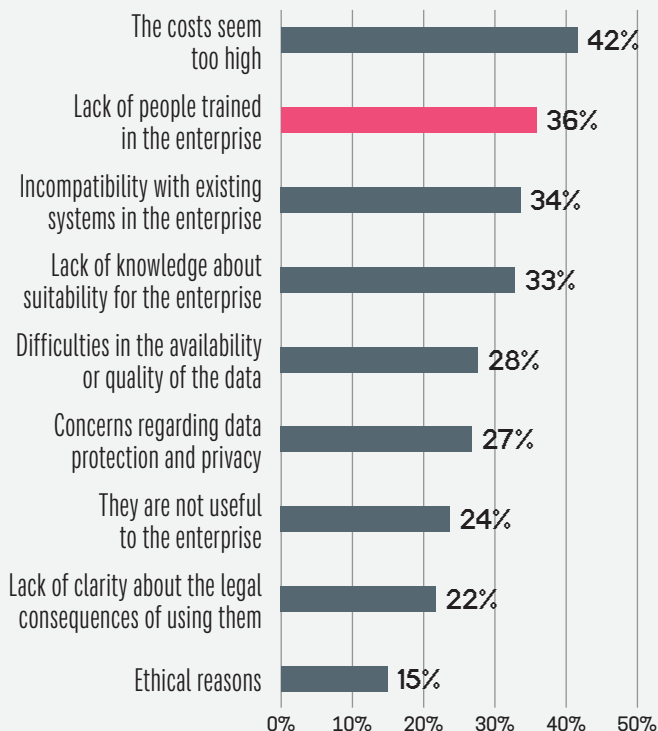
Data from the ICT Enterprises<sup>26</sup> and ICT Households<sup>27</sup> surveys show that a lack of skills is one of the main obstacles. Among large enterprises that do not yet use AI, 36% report that they do not have qualified professionals to work with these tools.<sup>28</sup> Similarly, among Brazilian workers who do not use AI, nearly one-third (32%) attribute this to a lack of skills to use it.<sup>29</sup>

## Reasons for not using AI: enterprises and workers

### Workers



### Large enterprises



<sup>24</sup> Data from the ICT Households 2025 survey, conducted by Cetic.br|NIC.br. Available at: <https://cetic.br/en/tics/domicilios/2025/individuos/M2/>

<sup>25</sup> Data from the ICT Enterprises 2025 survey, conducted by Cetic.br|NIC.br. Available at: <https://cetic.br/en/tics/pesquisa/2025/empresas/H9/>

<sup>26</sup> Find out more: <https://www.cetic.br/en/pesquisa/empresas/>

<sup>27</sup> Find out more: <https://www.cetic.br/en/pesquisa/domicilios/>

<sup>28</sup> Data from the ICT Enterprises 2025 survey, conducted by Cetic.br|NIC. Available at: <https://cetic.br/en/tics/pesquisa/2025/empresas/H13/>

<sup>29</sup> Data from the ICT Households 2025 survey, conducted by Cetic.br|NIC.br. Available at: <https://cetic.br/en/tics/domicilios/2025/individuos/M3/>

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## ABOUT CETIC.br

The Regional Center for Studies on the Development of the Information Society – Cetic.br (<https://www.cetic.br/en/>), a department of NIC.br, is responsible for producing studies and statistics on the access and use of the Internet in Brazil, disseminating analyzes and periodic information on the Internet development in the country. Cetic.br acts under the auspices of UNESCO.

## ABOUT NIC.br

The Brazilian Network Information Center – NIC.br (<http://www.nic.br/about-nic-br/>) is a non-profit civil Entity in charge of operating the .br domain, distributing IP numbers, and registering Autonomous Systems in the country. It conducts initiatives and projects that bring benefits to the Internet infrastructure in Brazil.

## ABOUT CGI.br

The Brazilian Internet Steering Committee – CGI.br (<https://cgi.br/about/>), responsible for establishing strategic guidelines related to the use and development of the Internet in Brazil, coordinates and integrates all Internet service initiatives in the country, promoting technical quality, innovation, and dissemination of the services offered.

\*The ideas and opinions expressed in the texts of this publication are those of the respective authors and do not necessarily reflect those of NIC.br and CGI.br.



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