



CONTEXT

Artificial Intelligence in the Brazilian Economy

What the evidence reveals about growth, labor, and
technological development

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Suggested Citation: PORTAS, Isabela; PICHININ, Thais. Artificial Intelligence in the Brazilian Economy: What the evidence reveals about growth, labor, and technological development.

Contexto Reglab, n. 9. São Paulo: Reglab, 2026.

This study was commissioned by META. Reglab maintained independence in the design, analysis, and conclusions of the research. Learn more in our Methodology Annex.

Executive Summary

This study reviews 87 documents (2022–2026) on the economic impacts of Artificial Intelligence (AI) in Brazil. Key findings include:

Estimates point to gains but diverge on their scale: among the 87 documents reviewed, the study found no estimates of a net negative effect of AI on Brazil's GDP or aggregate productivity. The available results are positive, but vary according to the assumptions adopted about investment, technology diffusion, and the economy's absorptive capacity.

Realizing this potential requires greater investment and more equitable adoption: today, AI use is still concentrated in large firms — 41% adoption, compared with 11% among small firms — and in more digitalized sectors (Jung and Katz, 2025). Broadening the gains depends on complementary investments in skills, digital maturity, and productive capacity, as well as on conditions that allow smaller firms to incorporate the technology effectively.

Task reorganization, with no mass displacement so far: studies do not record net job destruction, but rather an uneven reorganization of tasks. Exposure rises almost linearly with education (42.7% among those with higher education vs. 10.2% among those with no schooling) and affects women, young people, and the financial sector more (Barbosa Filho, Feijó, and Peruchetti, 2026).

Brazil leads Latin America in AI but lags behind in economy and regulation: the US tops the AI ranking, while Brazil ranks 16th and Mexico 32nd (STANFORD HAI, 2025). One point of concern highlighted by the study is that Brazil and Mexico score close to zero precisely on the Economy, Policy and Governance, and Responsible AI pillars, revealing gaps in commercial AI adoption and in regulatory frameworks compared with the leading countries.

Table of Contents

1. Introduction	5
2. Methodology	6
3. Findings	8
3.1 Conditions and costs of adoption	8
3.2 AI and development in Brazil: growth, inequality, and global asymmetry	11
4. Analysis and Commentary	16
5. Conclusion	17
6. Directions – Future Studies	18
References	19
Reglab Methodology Annex	23

1. Introduction

The diffusion of Artificial Intelligence (AI) in the Brazilian economy is still at an early stage, and relevant data on this already exist:

- In 2023–2024, 13% of companies reported using AI, concentrated in large firms (38%) and in the Information and Communication sector (38%) ([CETIC.BR, 2025](#)); the jump to 17% in 2025 ([CETIC.BR, 2026](#)) suggests that adoption has yet to take off.
- Internationally, the [International Monetary Fund's AI Preparedness Index](#) places Brazil among emerging economies, below advanced economies on all four pillars of the index — digital infrastructure; human capital; innovation; and regulation (IMF, 2024). AI already operates in the country, but recently, unevenly across firm sizes, and modestly compared with more developed countries.
- Although a regional leader, Brazil ranks 22nd in the [Government AI Readiness Index](#) by Oxford Insights (2026), which assesses countries' capacity to implement, develop, and govern AI.

Adoption, however, is not impact: knowing that a fraction of firms use AI does not tell us whether it changes productivity, employment, wages, or GDP — and in this regard, the literature on Brazil remains fragmented: many studies still rely on calibrated models and simulated scenarios; the evidence on labor is more consistent but scattered, and rarely isolates Brazil from regional aggregates; and sectoral effects come mainly from case studies.

Research and statistics on AI are growing at a rapid pace, **with different methods, perspectives, and framings**. Some of these studies remain confined to academic debate; others gain prominence in the press or circulate widely on social media. In this environment, the challenge is not just finding information, but **organizing quality evidence, distinguishing projections from observed effects, and identifying what they allow us to conclude about the economic impacts of AI**.

This **study gathers and critically assesses the evidence produced between May 2022 and May 2026 on the economic impacts of AI in Brazil**. The period covers the recent expansion of large language models, accelerated after the launch of ChatGPT in November 2022. By organizing a scattered literature based on different methods, the research seeks to distinguish observed effects from projections, identify convergences and gaps, and clarify which conditions determine the country's capacity to turn AI adoption into productivity, growth, and better labor market outcomes.

What do we mean by the economic impact of AI?

The definition of economic impact follows the task-based framework of Acemoglu and Restrepo (2019), applied to AI by Acemoglu (2025). In it, technology affects the economy through three mechanisms:

- **Displacement:** AI starts performing tasks previously done by humans, reducing labor demand in those tasks. Occupational exposure indices (Felten et al., 2021; Cazzaniga et al., 2024a) indicate where AI capabilities overlap with the tasks of each occupation. They do not indicate, however, whether AI replaces or complements the worker, nor whether adoption is economically viable.
- **Productivity:** by reducing costs, automation expands output and raises labor demand in tasks that remain human. In these tasks, AI can also act as a tool, automating steps, organizing information, and supporting decisions — what Acemoglu (2025) calls task complementarity.
- **Reinstatement:** historically, employment growth has come from the creation of new tasks in which labor has a comparative advantage. In the long run, the balance between displaced and newly created tasks determines labor's share of income. Acemoglu (2025) stresses that not every new task has positive social value.

All three operate simultaneously and determine the aggregate impact of AI on GDP and productivity; the weight of each depends on the technology's capacity to raise productivity and on the speed at which new tasks are created (Acemoglu, 2025).

2. Methodology

Measuring the economic impacts of AI requires dealing with a literature that is recent, scattered, and methodologically heterogeneous. **The available studies use different units of analysis, indicators, geographic scopes, and time horizons.** They also combine observed data, business surveys, occupational exposure indices, case studies, economic models, and projections.

Without a structured search and assessment procedure, there is a risk of **comparing results that measure different phenomena** (*"comparing apples and oranges"*) or **selecting only the evidence that confirms a prior interpretation** (*"cherry-picking"*).

To address this challenge, Reglab developed, based on Ferris et al. (2022) and Anderson and Reynolds (2020), a literature review protocol adapted from established systematic review practices and adversarial validation methods.

The design combines predefined inclusion and exclusion criteria, independent searches for positive and negative evidence, multi-stage screening, support from artificial intelligence tools, and human review.

The use of Blue Team and Red Team tracks seeks to reduce the risk of biased evidence selection. While one track searched for keywords related to productivity, growth, innovation, and job creation, the other investigated unemployment, inequality, market concentration, technological dependence, and environmental costs. The two tracks are conducted by different researchers, using the same search protocol, and are subject to the same screening criteria.

Blue team	Red team
Searched for evidence of positive economic impacts , focused on productivity, GDP growth, job creation, and sectoral efficiency.	Searched for evidence of negative economic impacts , such as unemployment, inequality, market concentration, technological dependence, and environmental impact.

The review was organized into three main stages — collection, screening, and analysis — and resulted in a **core database of 87 documents**. Materials relevant for contextualizing the debate, but which did not present direct or estimated evidence of economic impact, were kept in a separate database. This database is also not presented as an exhaustive, state-of-the-art review, but as a representative sample of a rapidly expanding universe.

Because the production of Brazil-specific evidence is still limited and a significant part of the literature analyzes the country within regional aggregates, the sample also included studies on Latin America and upper-middle-income economies. These results were used as comparative references and to identify mechanisms potentially relevant to the Brazilian context, without assuming that they can be automatically transferred across countries with different economic, institutional, and regulatory structures.

The following pages present a summary of the methodological process. The full protocol, including search strings and inclusion and exclusion criteria, is detailed in the **Methodology Annex**.

What this study analyzes — and what it does not

AI produces economic, social, political, legal, and cultural effects that cannot be adequately examined by a single study. **This study adopts a specific scope: it gathers evidence on the economic impacts of AI in Brazil**, focusing on productivity and growth, adoption by firms, labor market transformations, distribution of gains, economic concentration, and national technological capacity. Environmental impacts were considered when the literature linked them to economic costs or to the international distribution of benefits and externalities.

This framing does not assume that other consequences are nonexistent or less relevant. The study does not systematically assess issues such as data protection and privacy, algorithmic bias, information security, content integrity, or risks associated with specific AI applications.

Each of these dimensions requires its own questions, sources, and methods. The results presented, therefore, do not constitute a complete assessment of all the benefits and risks of AI, nor do they allow us to conclude that the technology is desirable or undesirable in general terms.

3. Findings

3.1 Conditions and costs of adoption

AT A GLANCE

- **AI adoption grows with firm size:** in Brazil, it reaches 41% of large firms, 24% of medium-sized firms, and 11% of small firms (Jung and Katz, 2025).
- **AI depends on prior digital maturity:** firms that already use cloud computing, big data, sensors, and other digital technologies are more likely to adopt it.
- **Education defines exposure in Brazil:** 42.7% of workers with higher education are exposed to generative AI, compared with 10.2% of those with no schooling or incomplete primary education (Barbosa Filho; Feijó; Peruchetti, 2026).
- **AI investment in Latin America remains low:** the region accounted for US\$11.59 billion in AI spending in 2023, equivalent to 3.7% of global demand (ECLAC, 2025).
- **Costs and gains are also concentrated:** the 20% of firms most exposed to AI recorded productivity growth of 163% between 2018 and 2025, compared with 34% across all AI-exposed firms (PWC, 2026).

3.1.1. Diffusion and adoption: who uses AI and why

Understanding the impacts of AI first requires understanding its adoption: what leads a firm to adopt it, under what conditions, and how its use spreads.

Diffusion is not homogeneous across countries, firm sizes, and sectors. [OECD \(2025\)](#) and [Jung and Katz \(2025\)](#) show a direct relationship between **firm size and the likelihood of adoption**: in the United Kingdom, 15% of small firms adopt AI, compared with 34% of medium-sized firms; in Japan, adoption ranges from 10% among the smallest to 48% among the largest. In Brazil the pattern repeats — 11% among small, 24% among medium-sized, and 41% among large firms — reflecting the advantages large firms have over smaller ones, such as resources, human capital, and a greater capacity to absorb risk.

Two other determinants are prior digital maturity and human capital. [Jung and Katz \(2025\)](#) and [Rosa and Kubota \(2025\)](#) show a hierarchy in the adoption of digital technologies: AI depends on earlier layers — sensors and IoT to see what is happening, big data and cloud to understand why, and only then AI as a predictive layer. **There is also a spillover effect: the more digitalized the sector, the region, and the firm size, the greater the adoption.**

The talent shortage is a significant global barrier. According to the [“IBM Global AI Adoption Index” \(2023\)](#), lack of skills is the biggest obstacle (33%) among IT professionals at large firms. The [OECD \(2025\)](#) shows that the problem is broader: 85% of European Union firms cite hiring qualified staff as the main barrier, and even among large firms ~17% cannot find suitable candidates.

At the macro level, two factors define what AI can do in each country: how much of the task structure it reaches (exposure) and how well equipped the country is to absorb it (preparedness) ([Cerutti et al., 2025](#)). Exposure is 60% in advanced economies, 42% in emerging economies, and 26% in low-income countries; the bottleneck for emerging economies is the combination of intermediate exposure with low preparedness. Latin America and the Caribbean invested US\$11.59 billion in AI in 2023 — 3.7% of global demand, seven times less than the US ([ECLAC, 2025](#)).

Data from the [“Brasil Digital”](#) report (2022) show that although **Brazil has an advanced institutional foundation for digitalizing public services, it still faces structural bottlenecks in connectivity and education that may limit the scale of this transformation.**

3.1.2 Human capital and skills

Who benefits from AI — through productivity and wages — depends less on access and more on education. The [FGV/IBRE](#) report shows that exposure to generative AI in Brazil rises almost linearly with education: 42.7% among workers with higher education versus 10.2% among those with no schooling (Barbosa Filho; Feijó; Peruchetti, 2026). The [IME](#) confirms this: in Brazil and the United Kingdom, more than 85% of workers with higher education hold

high-exposure jobs — but only 17% of Brazilian workers have higher education, compared with 36% in the United Kingdom (Cazzaniga et al., 2024b).

3.1.3 Economic and environmental costs of AI-driven growth: energy and concentration

AI growth carries an energy and environmental cost. [Carelli, Pereira, and Souza Júnior \(2024\)](#), drawing on the IEA, note that data centers already account for 0.3% of global CO₂ emissions (150 million tonnes per year) and consumed between 240 and 340 TWh in 2022 — equivalent to 1.3% of the world's electricity. [ECLAC/CENIA \(2025\)](#) projects that data center electricity consumption, currently around 1% of global electricity, could reach 8% by 2030 without efficiency gains.

In Brazil, where the type of energy mix may significantly affect these global estimates, evidence is scarce, but a few studies stand out: the IP.rec report [IA, Data Centers e os Impactos Ambientais](#) (AI, Data Centers and Environmental Impacts; Fernandes et al., 2025) acknowledges that although Brazil has a largely renewable energy mix, these sources are intermittent, requiring supplementation from non-renewable sources to ensure the continuous operation of data centers — a factor typically absent from global consumption estimates. The study also points out that the lack of regulation undermines the responsible growth of the sector, and that only through a robust and transparent regulatory framework will Brazil be able to establish itself as a benchmark in the adoption of sustainable digital infrastructure practices.

A second cost is market concentration — a dynamic that AI tends to **intensify**, not correct. *Superstar firms* (leaders that capture a disproportionate share of value in their sectors) are associated with higher GDP, but with concentrated gains: [Autor et al. \(2020\)](#) attribute to them a significant part of the decline in labor's share of income in the US. This concentration occurs at two scales. Across countries: in the sample of [Bustelo, Pérez, and Torrez \(2025\)](#), the top 100 global *superstar firms* are located in just 18 countries — 60 in the US and none in Latin America — precisely the countries leading in AI development. And across firms, this is where AI appears as an **accelerator**: according to [PwC \(2026\)](#), the 20% most exposed to AI — which the consultancy itself calls "superstars" — achieved 163% productivity gains between 2018 and 2025, compared with 34% across all AI-exposed firms.

3.2 AI and development in Brazil: growth, inequality, and global asymmetry

AT A GLANCE

- **Productivity falls short of expectations:** projections of trillions of dollars are not confirmed by measured data; more rigorous estimates point to only ~0.53–0.66% gains over 10 years in the US (Acemoglu, 2025).
- Latin America and Brazil: **the region suffers from a long-standing productivity bottleneck** (0.5% per year vs. 4.2% in East Asia); a Reglab study (Costa Filho; Palanca, 2026) projects R\$986.7 billion added to Brazil's GDP by 2030, with slow and gradual adoption.
- **In Brazil, the financial sector leads in AI exposure** (90.6%), while agribusiness is the least exposed (1.5%) (Barbosa Filho; Feijó; Peruchetti, 2026).
- **The impact of AI on work is heterogeneous and multifaceted**, combining displacement risks with productivity gains (Cazzaniga et al., 2024b).
- **In Brazil, informality (42% of the labor force) is the main driver of vulnerability**, creating the risk of a "double blow": job loss combined with loss of social protection (Cazzaniga et al., 2024b).
- **Asymmetries also run along gender and race lines:** women are more exposed to generative AI (35.4% vs. ~25% of men in Brazil) (Barbosa Filho; Feijó; Peruchetti, 2026); race is little studied, but digital exclusion disproportionately affects Afro-Brazilians (10.6 million without internet coverage) (IDB, 2024).
- **Brazil occupies a position of global technological dependence:** it is a consumer, not a producer, of AI, as it has few patents (Grohmann et al., 2025), low R&D investment, and data infrastructure concentrated in foreign capital (*hyperscalers*) (Carelli, Pereira, and Souza Júnior, 2024).

3.2.1 Economic growth and productivity

AI has generated high expectations, fueled by projections of trillions of dollars added to world GDP ([Acemoglu 2025](#)). But measurements of what has actually happened to productivity are far more modest — and this gap between the projected and the measured is itself a finding.

[Daron Acemoglu \(2025\)](#) estimated AI's contribution to growth with a more careful model: the impact depends on how much of the economy it reaches and how much it reduces costs. Using US data, he arrives at a maximum of 0.66% in total factor productivity gains over ten years — probably an overestimate, since it relies on tasks in which AI already performs well; when tasks requiring judgment and context are incorporated, the projection falls to ~0.53%.

This gap reinforces the "modern productivity paradox," in which technological progress is not immediately reflected in macro indicators ([Parteka and Kordalska, 2023](#)). Evidence from the

OECD ([Calvino, Reijerink, and Samek, 2025](#)) confirms real returns, albeit heterogeneous and context-sensitive.

In Latin America and Brazil, AI runs up against a historical productivity bottleneck: output per worker grew only 0.5% per year in the region between 1997 and 2022, compared with 4.2% in East Asia and 1.4% in the US ([Bakker et al., 2025](#)). Using a regional model, [ECLAC \(Jung and Katz, 2025\)](#) that calculates that each 1% of AI spending is associated with a small effect — about 0.036% of GDP — mainly through skilled labor, which would be equivalent to about US\$5 billion per year in Brazil.

In the long run, [Bakker et al. \(2025\)](#) project that, if the gap in AI usage intensity relative to rich countries follows the historical pattern of previous technologies, compounded by the region's lower exposure to AI, Latin America's growth rate in 2050 would be about 65% of that of the US; halving this gap, in both exposure and usage intensity, would allow the region to overtake the US before 2050. Another study that draws a parallel and projections with US data is the ["Brasil Digital"](#) report (2022), which presents an aggregate measurement exercise and estimates a gain of R\$422.7 billion to R\$1.12 trillion in GDP if the "digital supply" reached US levels — contextual data, not a causal estimate of AI's effect ([Estudo Brasil Digital, MBC/FGV, 2022](#)).

Unlike this correlational exercise, a study by [Reglab \(Costa Filho; Palanca, 2026\)](#) extends Acemoglu's (2025) model, simulating the impacts of productivity increases in both Brazilian labor and capital using categories of task and patent exposure and complementarity to AI. The result is an increase of R\$986.7 billion in Brazil's GDP by 2030, representing 7.6% of the GDP projected for 2026. The study assumes that productivity gains would materialize slowly and gradually, reaching 66.6% and 62.4% for labor and capital, respectively, in 2030.

3.2.2 Labor market and inequalities

According to the [ILO \(2025\)](#), about one in four workers worldwide (25%) is in occupations with some degree of exposure to generative AI — but only **3.3% of global employment** falls into the highest exposure band, the one with real automation potential. Exposure is higher among women: in high-income countries, 9.6% of female employment is in this highest exposure band, compared with 3.5% of male employment. Even so, the report stresses that the most likely effect is not the elimination of jobs but the reorganization of tasks: since most occupations combine automatable activities with activities that require human judgment, AI's gains tend to lie less in substitution and more in complementing human expertise ([Gmyrek et al., 2025](#)).

In Latin America, [Gmyrek et al. \(2024\)](#) estimate that between **30% and 40% of jobs** are exposed to generative AI (26% to 38%, depending on the country) — most of it with ambiguous or augmentation potential rather than direct automation (the latter accounting for

only 2% to 5% of employment). The authors acknowledge that the index may either underestimate or overestimate exposure in less developed economies. Even so, the results indicate that formal, urban, more educated, and higher-income workers are the most exposed to automation — particularly women and young people in the financial, insurance, and public administration sectors. This places the **middle class at the center of the change**: it is the group with the highest levels of exposure in jobs and earnings. And even among jobs with productivity-gain potential (rather than substitution), access is unequal: about **17 million jobs** in 16 countries in the region (nearly 10 million men and 7 million women) miss out on the benefit due to a lack of digital infrastructure.

[PwC \(2026\)](#) describes a “two-speed” market: “professionalized” roles, in which AI demands more human expertise, and “democratized” roles, made more accessible — the former grew in jobs twice as fast. [Huo, Ruan, and Cui \(2024\)](#), in a study on manufacturing in China, show a “U”-shaped curve: an initial predominance of substitution (with greater vulnerability among the low-skilled) and job creation in the long run.

In Brazil, [Acypreste \(2022\)](#) finds that, between 2000 and 2015, technological progress was not the main determinant of unemployment — most sectors created jobs. More recently, [FGV/IBRE \(2026\)](#) estimated that 29.6% of the employed population (~30 million) have some degree of exposure to AI, of whom 18% (5.2 million) are highly exposed, concentrated among women, young people, the more educated, residents of the Southeast, and the services sector.

The most affected sectors in Brazil are finance and technology: in 2025, banks allocated R\$826 million specifically to AI, within a technology budget of R\$46.8 billion, with R\$50.4 billion projected for 2026 ([FEBRABAN; DELOITTE, 2026](#)), and financial intermediation leads occupational exposure to generative AI, at 90.6% ([Barbosa Filho; Feijó; Peruchetti, 2026](#)) — a pattern confirmed by the [IBM Global AI Adoption Index](#).

Among the concerns is that AI may widen inequalities at work. [Pizzinelli et al. \(2023\)](#) analyze advanced and emerging economies and find a multifaceted picture: risk of displacement, but also productivity gains and complementarity, especially in high-level cognitive tasks. Because they concentrate skilled occupations, advanced economies tend toward a more polarized impact — greater gains and greater risk of substitution.

Comparing Brazil and the United Kingdom, [Cazzaniga et al. \(2024b\)](#) show that impacts vary with the worker's profile and the country's income level. In both, higher education is a converging factor: skilled workers move from high-exposure jobs to roles in which AI boosts productivity — a dynamic that benefits young people but may also pose a risk if AI reduces entry-level positions with low complementarity and high exposure.

In Brazil, [Cazzaniga et al. \(2024b\)](#) identify informality — 42% of the labor force — as a central driver of vulnerability, with the risk of a “double blow,” especially when disruption

involves a period of unemployment: the worker is pushed into the informal sector, simultaneously losing formal employment and social protection, in addition to an immediate wage penalty and slower earnings growth over time.

[Bakker et al. \(2025\)](#) show heterogeneity between the formal and informal sectors: in Peru's household survey (ENAH), exposure is 60% in the formal sector and 25% in the informal sector — the formal sector being close to the level of advanced economies. Informality implies smaller scale, less training, and less competition, reducing the exposure of the Latin American labor force.

While traditional automation affected manual production, AI reaches cognitive and office work in the formal, urban sector ([Gmyrek et al., 2024](#)). The impact is asymmetric: the more educated use AI as a complement; lower-skilled support and customer service occupations face a risk of substitution — and informality remains an obstacle to absorbing the benefits.

The relationship also works in reverse: adoption can deepen informality. Delivery platforms show how the use of algorithms in labor management intensifies precarious and informal work. The algorithms of these platforms, such as iFood, are used to mediate work, allocate tasks, and manage couriers' time, but without a formal employment relationship and its guarantees ([Silva, 2023](#)).

In short, the impact of AI on work is not homogeneous: it distributes positive and negative outcomes across occupations, education levels, age groups, and social groups, and cannot be reduced to simply increasing or reducing inequality.

Asymmetries are also expressed along gender and race lines. [Gmyrek et al. \(2025\)](#) compare 2023 and 2025 and show that women's exposure, in high-income countries, to occupations with high automation potential rose from 7.8% to 9.6%, compared with 2.9% and 3.5% among men. These figures indicate partial automation of tasks, not the immediate elimination of occupations — so AI may either generate unemployment or raise the productivity of these groups. In Brazil, the relationship also appears: according to [FGV/IBRE \(Barbosa Filho, Feijó, and Peruchetti, 2026\)](#), in the third quarter of 2025, 35.4% of employed women were exposed to generative AI, almost 10 percentage points more than men (~25%).

A counterpoint: according to [Ferreira and Castilho \(2025\)](#), under the classic automation metric (not generative AI), men have a higher probability (56%) than women (42%) — mechanical automation affects manual roles, which are more male-dominated, while generative AI affects cognitive tasks. Sectors such as domestic services (91% women) have low automation under both metrics, but perpetuate the concentration of women in the “care economy.”

Race is another axis, although little covered in the texts analyzed. According to the [IDB \(2024\)](#), 10.6 million Afro-Brazilians lack internet coverage, and most of those who do have

access do so only via mobile phone, relying on data plans. In addition, they are concentrated in low-wage formal sectors — construction (63.3%) and hospitality/food services (50.8%) — which rules out remote jobs and limits digital inclusion ([Irazábal Briceño, Serrano, and Santana, 2024](#)).

3.2.3 Technological dependence and global asymmetry

The global trajectory of AI repeats the core-periphery pattern: the capacity to produce AI — models, patents, and computing — is concentrated in the US and China, while Latin America, including Brazil, remains a consumer. According to [ECLAC \(2024\)](#), the region records only 1.2 AI patents per million inhabitants, compared with 60.4 in the US. Investment follows the same pattern: although it accounts for 6.6% of world GDP and 8.8% of the world's population, the region receives only 1.12% of global AI investment, and none of its countries exceeds the world average for AI investment relative to GDP per capita ([CENIA; ECLAC, 2025](#)). At the technological frontier, the US produced 59 notable AI models in 2025 and China 35, while Latin America remains virtually absent from this count ([Stanford HAI, 2026](#)).

Against this backdrop, [Grohmann et al. \(2025\)](#) offer a counterpoint: AI patent applications in Brazil rose from 150 in 2010 to 550 in 2019, but the increase is still modest compared with other regions over the same period — Europe, for example, recorded 10,500 and the United States 43,000. Moreover, the 20 largest patent applicants in Brazil are foreign-owned (from the US, Europe, Japan, India, and China), relegating Brazilian firms to a secondary role in AI development.

The same asymmetry exists in the deployment of data centers in Brazil. There are currently 554 data centers in Brazilian territory — 465 private and 89 public — most heavily concentrated in the state of São Paulo, and Brazil is the sector leader in Latin America ([Brandão; Lins, 2025](#)). Investment comes mainly from global *hyperscalers* and foreign capital: Microsoft announced R\$14.7 billion over three years and AWS R\$10.1 billion through 2034 — investments that, according to Brandão and Lins (2025), may generate socio-environmental impacts and privacy risks. A more recent example reinforcing this external dependence was TikTok's announcement of a R\$200 billion investment to build data centers at the Pecém port complex in Ceará. As a result, Brazil absorbs the labor and environmental costs, while financial gains and the data remain concentrated in more developed countries ([Carelli, Pereira, and Souza Júnior, 2024](#)).

4. Analysis and Commentary

This section analyzes the results in light of this study's findings and the authors' perspectives.

The results of this review support neither the expectation of an automatic economic transformation driven by AI nor the conclusion that its effects will be small. They point to a more conditional interpretation: AI can generate significant gains, but the **scale, speed, and distribution of these gains depend on the economic structures on which the technology is adopted.**

The problem is not just “about AI”: it is about long-standing socioeconomic bottlenecks. The technology exposes a broader issue in the development process: countries and firms with low investment capacity, technological dependence, insufficient human capital formation, and less control over infrastructure and intellectual property tend to incorporate innovations under disadvantageous conditions.

This means that AI does not create these asymmetries on its own, but builds on them and may amplify them. Brazil's challenge, therefore, is less about keeping up with an isolated new tool and more about strengthening the economic, productive, and institutional foundations that determine how each technological cycle is absorbed and how much value remains in the country.

Another important finding concerns **the urgent need to increase the production of evidence on AI in Brazil.** Brazil's gap lies not only in the number of studies, but in the type of evidence produced. The available literature mainly measures adoption, occupational exposure, and macroeconomic scenarios, and **studies that observe how the actual use of AI changes firms and career paths over time** are still rare. There is a lack, for example, of experiments and evaluations within firms that measure productivity, quality, learning, working hours, and task reorganization; behavioral economics research on trust, verification, delegation, and overreliance on AI outputs; and datasets linking technology adoption to hiring, wages, financial results, and career mobility.

However, this is not an exclusively Brazilian problem. Even the international literature still lacks consistent measures of usage intensity, complementary investments, intangible capital, and medium- and long-term effects. This is therefore a gap that needs to be filled in order to better guide public policy and medium- and long-term investment.

5. Conclusion

What did we set out to answer with this study?

This research sought to understand what the available evidence allows us to say about the economic impacts of artificial intelligence in Brazil. Rather than simply gathering projections or isolated indicators, the study organized a literature produced through different methods, separating observed effects, statistical associations, and estimated scenarios. **The aim was to identify not only whether AI can generate growth, productivity, and transformations in work, but also which conditions influence the scale and distribution of these outcomes.**

And what did we find?

The evidence indicates that the economic effects of AI are positive, but conditional and unequal. The technology is already being adopted, but it is first incorporated by firms, sectors, and workers that already had more resources, skills, and digital maturity. In the labor market, studies mainly point to task reorganization, with simultaneous possibilities of substitution and complementarity. On the technological front, Brazil has market scale and adoption capacity, but still participates only to a limited extent in the development stages and in capturing higher value.

These results do not allow us to conclude that the gains will remain concentrated, but they show that a broader distribution will not necessarily happen spontaneously.

And why does this matter?

The economic debate on AI cannot be limited to the speed of adoption. The capacity to turn the technology into productivity, better jobs, and development depends on broader issues in the Brazilian economy, such as vocational training, infrastructure, formalization, investment, innovation, and national productive capacity. AI does not create these bottlenecks on its own, but it operates on them and may amplify them.

For this reason, regulatory, industrial, educational, and tax policies need to act in a coordinated manner: not only to increase the use of the technology, but to broaden who is able to use it, produce knowledge from it, and capture the economic benefits generated in the country.

6. Directions – Future Studies

The recent nature of the phenomenon imposes limits on this research, which also point to future avenues:

- **Validation with observed data and longitudinal studies:** since part of the evidence on productivity relies on projections and calibrated models, longitudinal studies with observed data on productivity, employment, and income could test the projections against actual impacts over time.
- **Deeper research on race and gender inequalities and intersectional impacts:** given the scarcity of racial data, in contrast to the robust data on gender and education, we recommend dedicated research on the intersection of race, gender, and technological exposure, replacing qualitative inferences with original empirical evidence.
- **Primary research on informal and platform work:** most findings on informality come from formal-sector data. Studies with primary data on informal and platform workers could test whether the role of informality as a barrier or as protection holds up.
- **Assessment of the economic and regulatory impacts of Bill 2338/2023 (PL 2338/2023):** with the regulatory landscape in transition, empirical analyses of the concrete economic effects of Bill 2338/2023, once it has passed through the legislative process, would make it possible to move from mapping the disputes to actually measuring the impacts of regulation.
- **Measuring the environmental costs of AI infrastructure in Brazil:** given the specific nature of Brazil's energy mix — mostly renewable, but dependent on supplementation due to intermittency — studies are needed to quantify the electricity consumption and emissions associated with data centers in the country, which are currently absent from global estimates.
- **AI absorptive capacity of small and medium-sized enterprises:** with only 11% of small Brazilian firms adopting AI, compared with 41% of large firms, research on the specific barriers related to credit, skills, and digital maturity faced by SMEs would help design more targeted diffusion policies.

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Reglab Methodology Annex

AUTHORSHIP	Isabela Afonso Portas, Thais Ortega Pichinin, and Natália Ribeiro
Title	Artificial Intelligence in Brazil: evidence of economic impacts between 2022 and 2026
Research Question	What evidence on the economic impacts of artificial intelligence in Brazil was produced between 2022 and 2026?
Methodology Summary	Through a systematic literature review, the study investigates the evidence of the economic impact of artificial intelligence in Brazil between 2022 and 2026. The methodology combines documentary and secondary data analysis (<i>desk research</i>) with qualitative content analysis. Source collection was organized into two independent tracks: <i>Blue Team</i> (positive impacts) and <i>Red Team</i> (negative impacts), followed by multi-stage screening (AI-automated and human review) and inductive classification of the evidence into three thematic axes: productivity and economic growth, labor market, and strategic sectors.
Data Collection	Collection carried out from June 12 to 22, 2026, through a systematic search with predefined strings in Portuguese, English, and Spanish, divided between the Blue Team and the Red Team. <i>Blue Team — evidence of positive impacts</i> Search for evidence of productivity, economic growth, job creation, innovation, and sectoral gains. PT "inteligência artificial" AND ("aumento de produtividade" OR "crescimento econômico") "inteligência artificial" AND ("geração de novos empregos" OR "qualificação profissional") "inteligência artificial" AND "aumento do PIB" "IA" AND "pequenas e médias empresas" AND "impacto positivo" "inteligência artificial" AND "aumento de eficiência" EN "artificial intelligence" AND ("productivity increase" OR "economic growth") "artificial intelligence" AND ("job creation" OR "skills development") "artificial intelligence" + "GDP growth" "AI" AND ("small businesses" OR "SMEs") AND "positive impact" "artificial intelligence" AND "efficiency" ES "inteligencia artificial" AND ("incremento de productividad" OR "crecimiento económico") "inteligencia artificial" AND ("creación de empleo" OR "capacitación profesional") "inteligencia artificial" AND "crecimiento del PIB" "IA" AND ("pequeñas empresas" OR "pymes") AND "impacto positivo" "inteligencia artificial" AND "eficiencia" <i>Red Team — evidence of negative impacts</i> Search for evidence of unemployment, inequality, market concentration, technological dependence, and environmental impact. PT "inteligência artificial" AND ("gera desemprego" OR "deslocamento de trabalhadores")

"inteligência artificial" AND ("aumento de desigualdade" OR "concentração de mercado")
 "IA" AND "aumenta desigualdade de gênero" AND "mercado de trabalho"
 "inteligência artificial" AND "dependência tecnológica"
 "inteligência artificial" AND ("impacto ambiental" OR "consumo energético")

EN

"artificial intelligence" AND ("unemployment" OR "worker displacement")
 "artificial intelligence" AND ("increase inequality" OR "market concentration")
 "AI" AND ("gender gap" OR "impact on women") AND "labor market"
 "artificial intelligence" AND "technological dependence"
 "artificial intelligence" AND ("environmental impact" OR "energy consumption")

ES

"inteligencia artificial" AND ("aumento de desempleo" OR "desplazamiento de trabajadores")
 "inteligencia artificial" AND ("desigualdad" OR "concentración de mercado")
 "inteligencia artificial" AND ("brecha de género" OR "impacto en mujeres") AND "mercado laboral"
 "inteligencia artificial" AND "dependencia tecnológica"
 "inteligencia artificial" AND ("impacto ambiental" OR "consumo energético")

Search sources: Google Scholar (via Publish or Perish), Consensus, IPEA and IBGE databases, and AI research tools (Claude, Gemini, and Perplexity in Deep Research mode).

Geographic scope: Brazil as the main focus, complemented by Latin America and upper-middle-income economies (World Bank classification, 2025–2026).

Time frame of included publications: May 2022 to May 2026.

Raw result of manual collection: 131 records (Red Team, 3 duplicates across databases), 101 records (Blue Team), and 11 additional suggestions from the researchers, drawn from references of the Futuros Criativos (Creative Futures) project (Reglab).

Screening of material:

Screening followed four stages after the raw collection.

- Phase 1 (AI screening): automated application of the criteria for geographic scope, time frame, source type, and thematic relevance, resulting in 148 sources retained, 97 excluded, and 2 inconclusive (inaccessible links, flagged for human review).
- Phase 2 (human review): manual review by two researchers, with one recorded divergence from the AI screening: documents on the environmental impact of data centers were retained, on the understanding that the topic has an indirect bearing on the economy, resulting in 82 Red Team sources, 78 Blue Team sources, and 11 researcher suggestions (171 in total).
- Phase 3 (2nd AI screening): exclusion of literature reviews and meta-analyses because they do not constitute primary evidence, reducing the database to 53 (Red Team) + 63 (Blue Team) + 11 (suggestions), minus 1 document duplicated across databases — 126 documents in total, forwarded to the analysis phase.

In Phase 4, it was then established that the documents to remain in the Evidence Database should produce, or analyze, primary data from which a measurable or estimated economic effect can be derived (productivity, employment, income, GDP, investment, inequality, sectoral effect); documents that did not meet this criterion would be moved to a second database, the Context Database — a criterion justified because the research question calls for evidence of economic impact, not theoretical interpretation, programmatic or regulatory agendas, syntheses of third-party literature, or content tangential to the topic. A first application of this criterion to the 126 documents resulted in 30 in the Context Database and 96 in the Analysis

	Database. A detailed reading of the abstracts then identified 15 additional documents containing keywords from the search protocol but lacking thematic alignment with the research subject (14 from the Context Database and 1 from the Analysis Database), reducing the compilation to 111 documents (16 context, 95 analysis). Finally, verification of two references cited in the original project proposal — Azuara, Ripani, and Torres (IDB, 2024) and Bakker et al. (IMF, 2025) — led to the inclusion of both in the Analysis Database; the subsequent review identified and excluded 1 document that turned out to be a literature review, 2 documents duplicating each other, and 7 restricted-access articles, incompatible with the protocol's open-access criterion. At the end of screening, we had: Context data = 16 Analysis data = 87 Compiled = 103
Data Analysis	After screening the material, a qualitative content analysis was carried out, with inductive classification of the inferences drawn from each source into three thematic axes (not mutually exclusive): productivity and economic growth; labor market; strategic sectors. The included references were organized in a consolidated spreadsheet with metadata on title, authorship, year, abstract, source type, and geographic scope. The initial exploratory reading of the database was assisted by AI (Claude), with subsequent human review of the classifications and inferences.
Bias Reduction Procedures	(i) Adoption of predefined inclusion and exclusion criteria before collection (geographic scope, time frame, and source type); (ii) Blue Team / Red Team model of independent searches, testing opposing interpretations of the economic effects of AI; (iii) prior and explicit definition of the concept of "economic impact of AI" (ACEMOGLU, 2025), to avoid implicit or divergent criteria among researchers during screening; (iv) non-automatic handling of inaccessible links — assessment based on available metadata and flagging for human review instead of automatic exclusion; (v) double human review of AI-automated screenings, recording divergences and their rationales; (vi) explicit separation between the Evidence Database (documents that produce or analyze primary data from which a measurable or estimated economic effect is derived) and the Context Database (documents tangential to the research subject), preventing programmatic or theoretical material from being treated as evidence; (vii) chronological record of all collection, screening, and classification steps, allowing any researcher on the team to reconstruct the methodological path.
Other Methodological Limitations	Part of the evidence on productivity and economic growth relies on calibrated models and simulations with parameters estimated from real data, not on observed data of realized effects; these findings are presented in the body of the report as projections rather than as observed empirical evidence, to avoid attributing undue certainty to these sources. The database excluded 7 articles identified as relevant but with restricted access (paywalled or institution-only), which may have left out relevant evidence from paid literature. The time frame (May 2022 to May 2026) excludes evidence published outside this window, even when it concerns related phenomena. The geographic scope prioritizes Brazil, Latin America, and upper-middle-income economies, which may underrepresent comparisons with high-income economies outside this group.

Software Use	Claude (Anthropic): support for automated screening of sources according to inclusion/exclusion criteria, initial exploratory analysis of the consolidated database, thematic classification, and assisted writing. Google Sheets: recording and consolidation of the databases at each phase of collection and screening. Google Docs: recording of the search protocol (Blue Team and Red Team), methodology record, text editing, spreadsheets, and formatting of the final report.
Ethical Guidelines	This research was funded by Meta Brasil. LGPD (Brazilian General Data Protection Law): the research did not involve the collection or processing of personal data of identifiable individuals; the data analyzed are secondary, from public, open-access sources (academic articles, institutional reports, and public policy documents). Privacy and confidentiality: the data used are in the public domain and were obtained from accessible sources, without violating the privacy or confidentiality of any individual or institution. Responsible use of public data: although the data analyzed are public, they were used responsibly and ethically, for the sole purpose of independent research. Methodological transparency: the research methodology was detailed and documented chronologically (search protocol, screening criteria, quantitative results of each phase), allowing any researcher on the team to independently validate the results. Non-discrimination: The research was conducted in a manner that respects diversity and avoids any form of discrimination.
Editorial Independence Statement	The authors designed, conducted, and analyzed the study independently, without any input or interference from the company, which also did not influence or interfere with the interpretation of the results. The authors retain full professional independence and responsibility for the content and conclusions of this work.

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