The Economic Dimension of Personalization

Measuring the Impact of Personalized Artificial Intelligence on the Brazilian GDP

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Suggested Citation: COSTA FILHO, J. R.; RAMOS, P. H. The Economic Dimension of Personalization: Measuring the Impact of Personalized Artificial Intelligence on the Brazilian GDP. *Reglab Policy Briefs No. 5*. São Paulo: Reglab, 2025.

Executive Summary

- **AI personalization is a cross-cutting economic driver:** Personalization based on Artificial Intelligence (AI) affects virtually all productive sectors — not just the technology sector.

- **Significant macroeconomic impact:** A simulation of a scenario in which AI-based personalization were prohibited indicates a 1.64% drop in Brazil's GDP by 2035, equivalent to R$ 855 billion in accumulated losses over 10 years.

- **Most affected sectors:** Industries that are more interconnected with other sectors would suffer the greatest impacts — such as oil refining, metallurgy, and agriculture — since losses propagate throughout production chains.

	THE 10 SECTORS MOST IMPACTED	dVA
1º	Manufacture of tobacco products	-1,913
2º	Oil refining and coking plants	-1,897
3º	Slaughtering and meat products, including dairy and fish products	-1,886
4º	Manufacture of biofuels	-1,883
5º	Sugar manufacturing and refining	-1,873
6º	Agriculture, including agricultural support and post-harvest activities	-1,871
7º	Other food products	-1,856
8º	Livestock production, including livestock support activities	-1,849
9º	Oil and gas extraction, including support activities	-1,821
10º	Electric power, natural gas, and other utilities	-1,813

- **Why this matters:** The study shows that AI personalization is more than a convenience feature — it is also a critical infrastructure for productivity. The data reveal that severe restrictions on the use of this technology would not only penalize the digital sector but would also generate systemic competitiveness losses in Brazil's core industries and agribusiness.

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1. Introduction

1.1. What is Personalization?

Defining the object of a research study is a complex task; in information science, this concern is known as *ontology* — the effort to build systems that classify and represent knowledge. In the case of personalization, this task is particularly challenging because it involves technical, economic, communicational, and even cognitive dimensions.

A systematic review published in 2022 analyzed 383 academic studies on personalization and concluded **that there is no clear consensus on what personalization is** (Chandra et al., 2022), since the term can be interpreted from different perspectives: as an organizational strategy, a technological capability, a human–system interaction, or a user experience — just to name a few.

In this study, we prefer to adopt the perspective of a communicational process, similar to the one proposed by Blom (2000): **personalization is the process that alters the functionality, interface, content, or distinctiveness of a system to increase its personal relevance for an individual.**

Although personalization is mostly associated with digital systems, **it predates the digital era**: it has been present in commercial and communication practices since the late 19th century, beginning with direct-mail marketing, followed by credit bureaus and credit-card loyalty programs, among other strategies. When a merchant sets aside products that a frequent customer might like and decides to show them upon the customer's arrival at the store, that action is also a form of personalization.

> *Personalization is not an isolated phenomenon of the digital economy, but a structural trend throughout the history of marketing: a reflection of the effort to convert human preferences into data and, at the same time, to optimize attention, efficiency, and engagement.*

Chandra et al. (2022) also examined several ways of classifying types of personalization, **noting that most studies organize them based on six criteria**: (i) what data are used; (ii) what is personalized; (iii) how it is personalized; (iv) who performs the personalization; (v) where the data come from; and (vi) how this is communicated to the customer.

In the context of this study and the Brazilian regulatory landscape, we can explore these categories as follows:

PERSONALIZATION – FORMS OF CLASSIFICATION

1. WHAT DATA ARE USED

Non-Personal Data: in this case, we can refer to the personalization of enterprise-use systems, in which data unrelated to natural persons are used to personalize the system (a model more common in industrial and B2B applications);

Personal Data: when the system uses data related to a natural person, identified or identifiable.

2. WHAT IS PERSONALIZED

Content: Adjustment of information, media, or materials displayed to the user, aiming for greater informational relevance and engagement. Examples: social media feeds, streaming recommendations, playlists on music services, recommended articles on a news portal.

Advertising and Marketing: Targeting of ads, commercial offers, or political messages. Examples: targeted digital ads, newsletters, exclusive promotions in apps, political campaigns, financial service offers.

Services and Products: Dynamic adaptation of interfaces, language, and functionalities of products or services, shaped according to each user's profile and behavior. Examples: apps that reorganize menus, games that adapt the gameplay experience, chatbots and virtual assistants that adjust their tone of voice, software with customized dashboards, wearables that provide health alerts.

Price and Access Conditions: Modulation of access conditions to goods, services, or public policies, such as prices, fees, or benefits. Examples: differentiated credit rates, actuarial analysis.

3. HOW IT IS PERSONALIZED (Kwon e Kim, 2012)

Mass communication (one to all): The system makes the same offer to everyone, based on general averages of preferences. In this case, there is no real personalization, only targeting based on general usage statistics.

Group segmentation (one to n): The company divides the audience into groups with similar characteristics (also known as clusters). This is, for example, the most common model in digital advertising — the offers are rarely made specifically for you, but rather for groups with similar characteristics.

Individual personalization (one to one): In this case, the personalization is done for each specific person, based on data, history, and behavior — like a recommended movie list on a streaming platform.

4. WHO PERSONALIZES

System Provider: The adaptation is carried out entirely by the organization that controls the system. In this model, business rules unilaterally define the user experience. Examples include credit limit assignments by financial institutions or shelf layouts in supermarkets.

User: The customization results from a manual and deliberate action by the individual themself, determining a priori how the system should behave or present information. This includes choosing add-ons when purchasing vehicles or configuring dashboards in ERP systems.

By the Provider, through User agency: An intermediate space in which the technical execution is carried out by the system and calibrated by explicit signals of user agency (such as feedback signals, control adjustments, or output corrections). Digital advertising and like/dislike tools in streaming services fall into this category.

5. WHERE DOES THE DATA COME FROM?

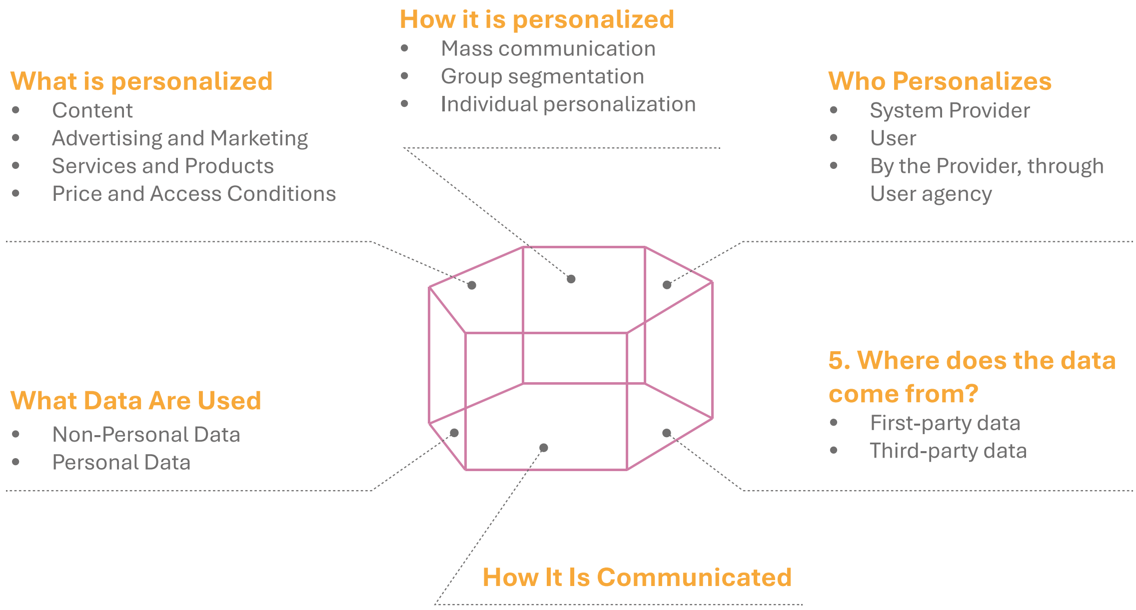
First-party data: Information collected directly by the organization during the user's interaction with its own channels and touchpoints. Example: a streaming service that recommends movies based on the user's viewing history and ratings on the platform.

Third-party data: Information obtained from sources that are external to the organization's direct relationship with the user, such as data brokers, business partners, or public sources, used to enrich profiles and infer behaviors. Example: a banking institution that uses credit scores provided by external credit bureaus.

6. HOW IT IS COMMUNICATED

In this case, a rigid classification would confuse more than help, since, in practice, what exists is a **spectrum of transparency**: a *continuum* that stretches from one pole of total opacity to the normative ideal of full transparency, with reality positioned in the multiple intermediate gradations of this spectrum.

- At the extreme of opacity, 'zero transparency' is currently incompatible with market requirements — which demand informational openness to the user — and with personal data protection laws, which expressly prohibit it.
- At the same time, absolute transparency is more of an axiological horizon than an actual reality, since the technical complexity of certain systems and the cognitive overload imposed on the user also make perfect intelligibility unattainable.



The interaction among these six dimensions produces different effects, and risks are not an intrinsic property of any isolated category, but rather the result of how they combine. A practice based on intensive personal data is not always the most sensitive, and the use of aggregated data is not always harmless — **the difference lies less in the type of technology and more in how these dimensions intersect.** To illustrate, let us compare two scenarios:

- A streaming system may use granular behavioral history from the user (one-to-one personalization with first-party data) to recommend a movie. The 'risk' in this case, if something fails, is merely a frustrating entertainment experience;
- On the other hand, a credit model may use no individual data at all, but instead set the interest rate based solely on your ZIP code or age group (cluster-based segmentation). Although this may seem less invasive, the material impact is infinitely greater;

In practice, starting this study by explaining all of this matters because the term 'personalization' has become a catch-all label used to justify everything from legitimate innovations to questionable practices. Without distinguishing what, who, and how something is personalized, which data are used and where they came from, and how this is communicated, the public and regulatory debate becomes shallow, decisions end up treating very different situations as if they were the same, and we miss the opportunity to identify where there may be real gains in efficiency and relevance for the user — a topic that becomes especially important in the context of the widespread adoption of artificial intelligence and machine-learning techniques.

1.2. AI and Personalization

In today's world, Artificial Intelligence (AI) plays the role of enabling large-scale personalization, allowing products, services, and experiences to be adjusted. Common examples include video or music recommendations, search engines that tailor results for each person, chatbots that adapt their language to the user's profile, and versions of webpages that change according to browsing history.

We have numerous examples of studies on the topic just from this year: Nisar (2025) analyzed how AI is transforming the interaction between consumers, companies, and services, focusing on recommendations and engagement. The Future of Privacy Forum (2025) report, *'Concepts in AI Governance: Personality vs. Personalization,'* distinguishes how *'personalization'* is treated in major Generative AI systems. Shafik (2025) discusses the impact of AI on digital marketing: machine-learning and natural-language-processing techniques enable individualized personalization, surpassing clustering, while Bitra (2025) explores the regulatory challenges resulting from this scenario.

Although the debate may seem recent, for decades different sectors have already adopted mechanisms for adapting content, products, and services to users' preferences. What changes with Artificial Intelligence is the **scale and depth** of this process: machine-learning techniques make it possible to personalize not only what is offered, but also **the very behavior of the systems** that interact with the user. Thus, personalization ceases to be a peripheral function and becomes the **central operating logic** of various digital products and business models.

> For the purposes of this study, we understand **AI technologies** as software systems capable of processing and analyzing data through algorithms and mathematical models, using statistical and computational techniques to identify patterns, make predictions, or generate new content. In other studies published by Reglab, we distinguish between **Analytical AI** systems, focused on solving well-defined problems such as fraud detection or demand forecasting, and **Generative AI** systems, capable of creating texts, images, or code from large volumes of data. Unless an explicit distinction is made in the text, this research encompasses both types of systems together, within the broader concept of AI technologies.

1.3. Economic and Regulatory Relevance

Time is money. If a tool (a hammer, an excavator, or software) helps perform a task faster, we save time, and **we call this gain an increase in productivity.** And studies on AI have consistently shown how these technologies increase productivity.

Brynjolfsson, Li, and Raymond (2025), Dell'Acqua et al. (2023), and Noy and Zhang (2023) were among those who documented significant gains when people began using Generative AI tools in their daily activities. Eloundou et al. (2024) estimated that about 80% of the U.S. workforce could have at least 10% of their tasks affected by the introduction of these technologies — 19% could have more than half of their tasks impacted, and about 15% of all tasks in the U.S. could be completed significantly faster while maintaining the same level of quality.

These numbers suggest that AI is not a niche technology that will affect only a few specialized sectors, but rather a general-purpose technology that will have broad impacts across the entire economy.

Part of these gains comes from the ability of these tools to adapt to each user — that is, **from their personalization.** When AI understands your way of working, it delivers results that are more useful and faster. Without this, you lose part of the advantages it offers.

EXPLAINING IN PRACTICE

Imagine that the AI learns how you like to write emails — whether you prefer a more direct or formal tone, whether you usually start with a specific greeting, whether you typically end with 'sincerely' or 'best regards.' Over time, the suggestions it offers already come 'in your style.' Two colleagues asking for the same thing will receive different responses, each adjusted to their individual way of communicating. This saves time — and increases productivity — because you don't need to rewrite as much.

But the absence of this personalization can cause problems that go beyond simply working more slowly. Recent research, such as the study conducted by Gadhvi et al. (2025), found that lack of personalization can **lead to a 17% reduction in worker satisfaction and a 10% reduction in focus on the tasks performed.** These numbers may seem abstract at first, but they have concrete and measurable implications for productivity

When we lose focus and switch from one task to another, part of our attention remains stuck on what we were doing before — and this harms our performance because our mind cannot completely shift focus right away (Leroy, 2009). With non-personalized AI tools, this happens all the time: you need to reinterpret the responses, make adjustments, and complete what the AI delivered. **If the tool knows your way of working, many of these adjustments would not be necessary.**

And the problem goes beyond losing focus. Mark, Gudith, and Klocke (2008) show that constantly jumping between tasks increases stress, frustration, and fatigue. In other words: non-personalized tools not only make work slower, but also more exhausting, less satisfying, and consequently less productive (Oswald, Proto, and Sgroi, 2015).

Finally, there is the issue of time. Dillon et al. (2025) found that using AI for emails can reduce the time spent on this task by 31%. This would free up almost four hours per week — time that can be used for more important activities. In a 40-hour work week, this represents a productivity gain of nearly 10%.

Potential Effects of the Non-Personalization of a System

Effect	Explanation	Empirical Evidence
Attention residue	When part of your mind remains 'stuck' in the previous task even after switching activities. This hinders your focus on the new task.	10% loss of focus (Gadhvi et al., 2025)
Fatigue and satisfaction	Jumping between tasks and correcting errors is more tiring and frustrating. The more exhausted you are, the less you produce. When you are satisfied, you work better and more.	17% loss of satisfaction (Gadhvi et al., 2025); more satisfied workers produce up to 12% more (Oswald, Proto, and Sgroi, 2015)
Time and productivity	Time saved on repetitive tasks can be used for important work. Less time wasted = more productivity.	Reduction of time spent on emails by up to 31% (Dillon et al., 2025)

Given this body of evidence, **would it be possible to estimate what the effect of the personalization of AI systems would be in economic terms?** To answer this question, we first need to establish a methodology that allows us to translate these individual productivity gains into aggregate economic impact.

2. Methodology

SUMMARY – HOW THIS STUDY WAS CONDUCTED:

- **Comparison scenario:** The study simulates an extreme case, as if there were a law preventing AI systems from using data to adapt to the user.
- **Reference value:** To measure this impact, we use a comparison value: with personalized AI, work yields 10% more; without personalization, it yields 10% less. In addition, there would be a 10% loss of focus. Together, these two effects result in a net loss of about 1% in total productivity.
- **Economic model:** The economy works like a network in which everything is interconnected. If one sector loses efficiency, it affects the others. For this reason, the study uses a general-equilibrium model, which shows how a loss in one area spreads throughout the entire economy.
- **Difference between sectors:** Not everyone uses AI in the same way. The study cross-referenced data on occupations and tasks with IBGE statistics to calculate which sectors would be most affected by a ban on personalization — and how much this would weigh on Brazil's GDP.

Methodologically, this study has **four relevant aspects:** a counterfactual scenario, a calibration parameter, the econometric model, and the calculation of AI-use exposure.

(i) Counterfactual Scenario: Non-Personalization

To estimate the macroeconomic effects of personalization, the model begins with a boundary hypothesis: a complete ban on personalization. This is not a prediction that such a scenario will materialize politically, but rather a methodological necessity to establish the 'total exposure' of the Brazilian economy. This choice, although seemingly extreme, is methodologically necessary.

> **EXPLAINING IN PRACTICE**
> Imagine a ruler: to measure any intermediate level, we must first define where the ruler begins and where it ends. That is why general-equilibrium models require clear quantitative anchors. Trying to model hybrid scenarios directly — such as opt-in (prior consent) or opt-out regimes — would require assuming behavioral premises about how many users would accept or refuse personalization, along with other elements that would themselves constitute an entirely new study. **By fixing the scenario at the maximum restriction (total prohibition), we calculate the 'ceiling' of the economic impact. This value therefore serves as a baseline reference:** any regulation or judicial/administrative decision that partially restricts personalization (whether through consent frictions, sectoral bans, or technical limitations) will entail an economic cost that is a fraction of this total impact.

Thus, **the extreme scenario works as a stress test:** it reveals the total size of the value at stake. If a milder regulation reduces personalization efficiency by only 20% or 50%, policymakers can use this study to infer the proportional costs, knowing that the real impact will lie somewhere along the gradient between the baseline scenario (full use) and this counterfactual scenario (no use).

(ii)) The Size of the Initial Impact: 1%

To estimate the economic impact of personalization performed by AI systems, we start from reference values adopted as calculation baselines — something common in economic studies that simulate scenarios that are still difficult to observe directly.

In this case, and based on the studies summarized in Table 1, we consider that **personalization generates an average productivity gain of 10%**, resulting from time savings and greater task precision. This also means that the absence of personalization **would cause a 10% loss in productivity**, associated with attention dispersion, lower user satisfaction, and reduced efficiency in task execution.

In practice, it is like comparing two production lines: one equipped with tools adjusted for each worker and another that uses the same standard for everyone — assuming that the first performs its tasks 10% faster than the second.

By combining these gain and loss effects, the study simulates **a net productivity shock** of –1% in tasks that could benefit from AI personalization.

EXPLAINING IN PRACTICE

1. Imagine that the initial productivity is 100
2. The use of personalized AI generates +10% → productivity rises to **110**.
3. If personalization is prohibited, there is a 10% loss on this **new value (110)** → 10% of 110 = 11.

Final result: 110 – 11 = **99**.

In other words, **productivity falls from 100 to 99, a net reduction of 1%.** It is worth noting that this value is not directly observed in reality, but serves as our *reference* for estimating the aggregate impact on the economy as a whole. And even so, it is a *conservative estimate*.

- This is because the calculation assumes that the negative effects of non-personalization only partially reduce the gains from AI, whereas in practice they may be larger and even hinder the completion of a task. Imagine an autocomplete system that, with every sentence, suggests incorrect terms that you then have to delete and rewrite — in other words, the tool not only fails to help but actually gets in the way, consuming time for corrections.
- Moreover, the model does not incorporate other benefits of personalization, such as learning Brazil-specific contexts, regional differences, or the reduction of 'rework' in complex activities. A generic AI may draft a flawless contract, but fail by ignoring the specific tax information of the contracting companies.

For this reason, the 1% shock should be interpreted as a minimum bound of the potential impact – a prudent way of measuring a phenomenon that is still unfolding. It is important to note that, given the differences across economic sectors, this initial shock could also vary among them: therefore, we assume that the degree of exposure to AI use already reflects these differences and, consequently, the resulting shock in each sector is (i) lower than 1% and (ii) specific to each sector, as presented later in the text.

(iii) The Quantitative Model: General Equilibrium

"Now that we have defined the scenario and the mathematical parameter, we need to translate this into macroeconomic impacts — that is, how much this represents, in reais, for different sectors of the Brazilian economy, which are not isolated but interconnected through a complex network of contractual and economic relationships. To capture these interdependencies, the most suitable framework is what we call a **general equilibrium model.**

EXPLAINING IN PRACTICE

Imagine the economy as a large network of companies that buy and sell from one another. An automobile factory, for example, does not only produce cars — it also buys steel from steelmakers, electronic components from specialized manufacturers, tires from rubber companies, and so on. If something affects the productivity of the automotive industry, this impacts not only the cars coming off the assembly lines, but also all the companies that supply inputs to that industry. Likewise, if the productivity of steelmakers falls, this makes steel more expensive, which in turn affects not only the automotive industry but also construction, home appliance manufacturing, and many other sectors.

A general equilibrium model is a mathematical representation of this network of relationships. It allows us to simulate **what happens when there is a change at some point in the economy and to track how that change propagates through the production chains.**

General equilibrium models are particularly well suited to capturing these cascading effects (Acemoglu et al., 2012; Carvalho, 2014; Carvalho and Tahbaz-Salehi, 2019). It is possible, for example, for a relatively small shock in a highly connected sector (one that influences several production chains) to generate amplified effects throughout the entire economy. An isolated sectoral analysis could estimate the direct impact of a productivity loss in the oil refining industry, but it would not capture how this loss affects fuel prices, which in turn impact transportation costs, which ultimately affect the competitiveness of virtually every other sector in the economy.

In our case, let's imagine that law firms lose access to personalized AI tools and start using generic versions instead. What could happen?

- Professionals may spend more time reviewing contracts and reworking analyses, which could lead to an increase in the fees they charge;
- Their clients — banks, construction companies, and industries — would receive opinions more slowly and at higher costs;
- Banks, in turn, might take longer to approve financing, delaying construction projects, and construction companies would purchase materials later, affecting suppliers of cement and steel;
- **And thus, however small it may be, the impact spreads: a loss of productivity among those who use AI to write and analyze information ends up spilling over into the entire production chain.**

In summary, the general equilibrium model allows the study to go beyond the initial 1% productivity shock. It makes it possible to estimate the final impact on the economy by taking into account all the complex interactions between sectors, the effects of the tax system, and the specific characteristics of Brazil's productive structure, as well as consumer responses.

(iv) The Degree of Exposure to AI Use

How does the lack of AI personalization directly affect each sector of the Brazilian economy? It would be incorrect to measure the macroeconomic effect assuming that all occupations within each sector have the same degree of exposure to these technologies.

To construct this sectoral exposure measure, we combine three different sources of information:

i. we use the **task exposure indices** developed by Felton, Raj, and Seamans (2021), which measure how much different types of tasks may be affected by AI;

ii. we combine these data with the **occupation-level exposure indices** from Cazzaniga et al. (2024), which estimate the share of tasks in each profession that could be affected by Large Language Models (LLMs); e, por fim,

iii. we use **data from the National Household Sample Survey (PNAD)** by the Brazilian Institute of Geography and Statistics (IBGE), referring to the last quarter of 2024, to determine the weight of each occupation within each sector of the Brazilian economy.

EXPLAINING IN PRACTICE

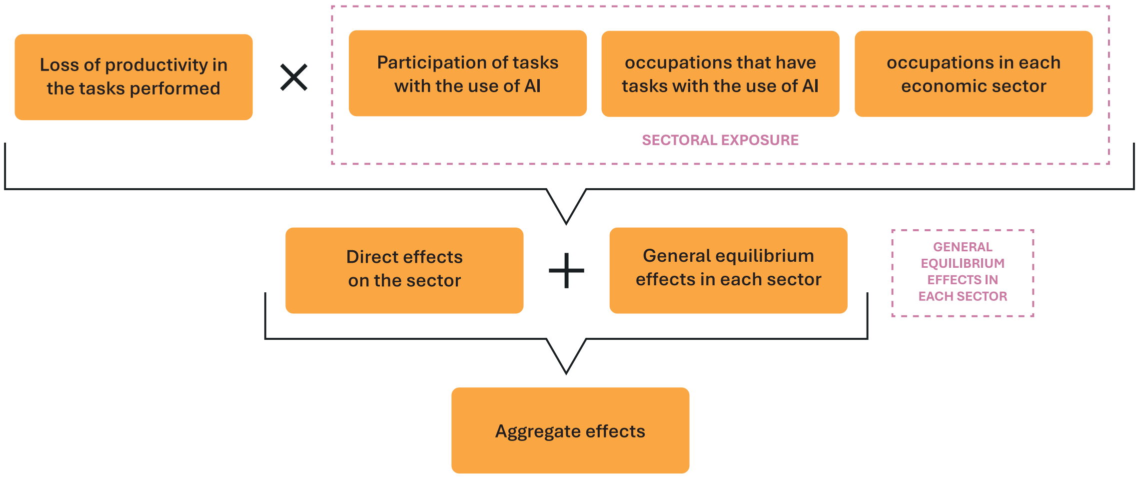
Each **occupation** (profession) has a different level of exposure to AI; moreover, the **tasks** performed within each occupation also have distinct levels of exposure.

Let's consider two occupations: journalists and doctors. For a journalist, tasks such as editing texts and transcribing interviews have high exposure to AI (that is, AI can potentially substitute these tasks), whereas building trust with sources and interpreting political nuances have much lower exposure (meaning AI is unlikely to substitute them). For doctors, tasks such as reading a simple imaging exam or organizing medical records are highly exposed, while talking with patients and making treatment decisions in complex situations have much lower exposure.

In this study, what we did was combine task-level exposure indices with occupation-level exposure indices, aiming for a more precise view of the reality of professions. Along with this, we determined the weight of each occupation in the Brazilian economy using data from the IBGE.

By combining the occupation-level exposure indices with data on the occupational composition of each sector of the Brazilian economy, the study was able to calculate a sectoral exposure measure, which indicates how much of each sector's economic activity could be affected by the productivity shock caused by the prohibition of personalization.

Figure 1 – Quantitative Analysis Diagram



Notes: Schematic representation of the quantitative analysis across three layers: (i) definition of the shocks in each sector — as a combination of productivity loss in tasks (a 1% decline) and sectoral exposure determined by the types of occupations within each sector of economic activity; (ii) simulation of the general equilibrium effects in each sector and the aggregate effects.

Note that the general equilibrium simulation conducted in this study does not consider possible dynamic changes in how AI is adopted over time, which reinforces the conclusion that the results represent conservative estimates of the impact of banning the personalization of AI tools.

The full methodology of this study is detailed in the Appendix.

THE REGULATORY LENSES OF ARTIFICIAL INTELLIGENCE

Debates on AI rarely start from a single regulatory lens. Each field – **competition, data protection, digital rights, economic development** – observes the same phenomenon through legitimate but distinct concerns. These approaches may appear divergent, **but in practice they are complementary:** each provides a specific instrument for advancing important public policy goals.

By situating this study within this plurality of lenses, the aim is to acknowledge that the economic perspective – focused on productivity, efficiency, and aggregate impact – **does not seek to replace, but rather engage in dialogue** with the other fields.

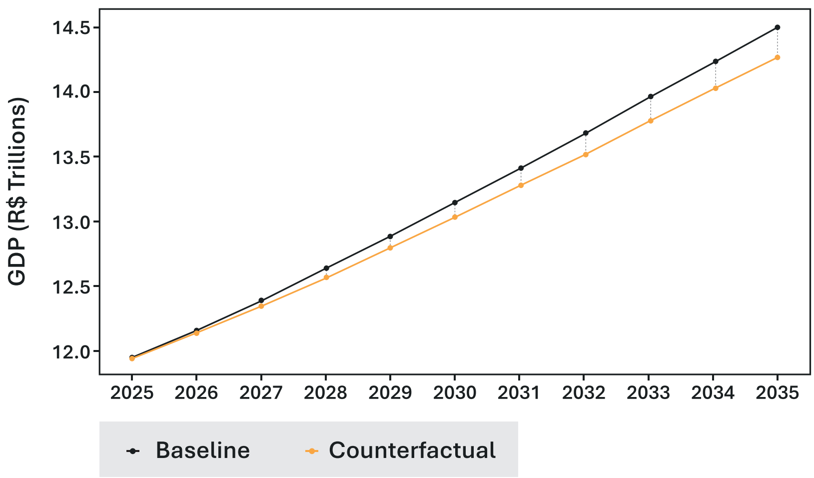
3. Results

3.1. Aggregate Macroeconomic Impact

When we introduce the shocks adjusted by sector-specific exposure into the general equilibrium model, the ban on AI personalization would lead to a **1.64% decrease in Brazil's Gross Domestic Product over a ten-year horizon**, compared with a reference scenario in which the technology can be fully utilized.

It is important to emphasize that the effect of the shock unfolds over time — not all at once. In other words, when calculating the trajectory of the counterfactual scenario, we considered the year-to-year decrease in the growth rate required to produce a GDP that is 1.64% lower in 2035. Figure 2 presents the comparison between the baseline scenario and the counterfactual simulation.

Figure 2 – GDP Scenarios Over a Ten-Year Horizon



Notes: The black curve represents the baseline scenario, and the orange curve represents the scenario generated by the general equilibrium model simulation.

> To put this into perspective, Brazil's GDP in 2024 was approximately R$ 11.7 trillion. A 1.64% drop in GDP ten years ahead represents an **accumulated loss** (that is, the loss of GDP in each year of the simulation up to 2035, discounted to present value and summed) **of R$ 855 billion.**

It is important to understand why this 1.64% impact is larger than the initial 1% productivity shock: **the model captures the cascading effects throughout production chains.** When a sector loses productivity, it not only produces less but also makes its products more expensive, which affects all sectors that depend on those products as inputs. These sectors, in turn, also become less competitive, and the effect continues to propagate.

3.2. Impactos Setoriais

	OS SETORES MAIS E MENOS IMPACTADOS	dVA
1º	Manufacture of tobacco products	-1,913
2º	Oil refining and coking plants	-1,897
3º	Slaughtering and meat products, including dairy and fish products	-1,886
4º	Manufacture of biofuels	-1,883
5º	Sugar manufacturing and refining	-1,873
6º	Agriculture, including agricultural support and post-harvest activities	-1,871
7º	Other food products	-1,856
8º	Livestock production, including livestock support activities	-1,849
9º	Oil and gas extraction, including support activities	-1,821
10º	Electric power, natural gas, and other utilities	-1,813
...	...	...
57º	Manufacture of clothing articles and accessories	-1,584
58º	Accommodation	-1,572
59º	Wholesale and retail trade	-1,564
60º	Artistic, creative, and performance activities	-1,562
61º	Other administrative activities and support services	-1,561
62º	Financial intermediation, insurance, and supplementary pension services	-1,554
63º	Publishing and publishing integrated with printing	-1,549
64º	Private healthcare	-1,495
65º	Systems development and other information services	-1,477
66º	Private education	-1,368

The sectoral analysis shows that the impact would not be distributed uniformly across the economy — and this reveals a pattern related to the structure of Brazil's productive system.

The sectors that appear at the top of the ranking are not necessarily the ones that use AI the most directly, **but rather those that are more deeply integrated with other sectors of the economy through input–output relationships** — that is, the interdependencies between sectors that arise both from using inputs produced by others and from supplying products that will serve as inputs elsewhere. Oil refining, the second most affected sector, supplies fuels and raw materials to petrochemicals, the plastics industry, and the entire transportation chain.

When these sectors lose productivity due to the ban on AI personalization, they reduce their demand for refined petroleum products, amplifying the impact on refineries. Similarly, agriculture supplies essential inputs to the food industry, biofuels, and various export products. As these downstream sectors face higher costs and reduced output, the demand for agricultural products also falls, multiplying the initial effect.

This propagation dynamic across production chains explains why highly integrated sectors experience disproportionately larger impacts: **they not only face their own productivity losses but also absorb the indirect effects of reduced demand from all the sectors with which they are connected.**

On the other hand, it may seem contradictory that sectors such as private education, private healthcare, or systems development are among the least affected. But this is explained by the productive structure and the nature of their inputs:

i. In these sectors, value added **depends heavily on the quality of decisions and on the interaction between people and specialized knowledge.** Therefore, even if AI-based personalization is restricted, there is room for human adjustments that compensate for part of the loss in efficiency.

ii. In addition, these sectors tend to have **relatively inelastic demand — healthcare, education, and financial services do not experience sharp drops in consumption as a result of technological changes.** The impact, therefore, is more diffuse and gradual, reflecting a greater structural resilience to digital productivity shocks.

iii. In the case of the systems development sector, there is a paradox: although AI personalizes digital products, **restricting personalization may generate additional demand** for adaptation, customization, and technical support services, which would sustain the sector's value added.

Looking again at the most adversely affected sectors, we see that these are highly integrated into standardized industrial chains and rely heavily on marginal efficiency gains. This means that:

i. **Even small productivity losses propagate throughout the entire supply chain**. In these activities, AI personalization plays an increasingly important role in quality control, demand forecasting, and logistical and energy optimization.

ii. When this optimization layer is removed, the impact is multiplied: it affects costs, waste, and deadlines, **directly reducing value added.**

iii. Moreover, **these are export-oriented sectors with narrow margins**, in which international prices limit the ability to pass on costs. Thus, any drop in efficiency reduces external competitiveness, amplifying the initial negative impact.

In summary, the results show **that sectors based on human capital and stable demand absorb negative shocks from AI personalization** more easily, while **sectors based on operational efficiency and production scale are more strongly affected.**

4. Analysis and Comments

4.1. The cross-cutting nature of AI and Personalization themes

The results of this study show **that personalized Artificial Intelligence is not a topic restricted to large technology companies.** AI cuts across virtually all productive sectors of the economy, from heavy industry to services. This diversity reveals that the debate on AI should not be treated merely as an issue of 'digital platforms,' but also as a structural challenge for economic efficiency and national competitiveness.

Sectors traditionally seen as distant from the digital world — such as oil and gas, and agriculture — increasingly depend on AI systems **to optimize processes, control quality, perform predictive maintenance, and analyze large volumes of operational data.** Moreover, they are more affected by systemic impacts in the economy precisely because of their central role in production chains.

What may be affected is not only the performance of technology companies, **but all of Brazil's production chains.** AI regulation, therefore, should be understood as a broad development policy — not merely as a digital policy.

4.2. Strategic Implications

The results of this study do not describe merely a loss of productivity. They reveal that discussing personalization — especially when we refer to personal data — **is also a discussion about economic policy and social well-being.** The evidence presented in this report shows that the use of data in AI should not be treated solely as a risk to be contained, but also as productive infrastructure that requires calibrated regulation and incentives for responsible adoption. Through the possibilities enabled by AI personalization, productivity gains emerge not only at the sectoral level but also propagate through complex production chains, generating benefits for the economy as a whole.

The challenge now is to translate these findings into concrete action, and to do so it is necessary to guide different audiences with messages that are distinct but complementary.

The Brazilian regulatory agenda is at a decisive moment. The debate on **Draft Bill 2338/23** (which regulates the use of AI), developments and interpretations of the **LGPD** in the courts and within the ANPD, the approval of the Digital Child and Adolescent Statute **(ECA Digital)**, and Bill 4675/25 (which regulates competition in digital markets) form a set of norms aimed at protecting rights and preserving fundamental guarantees, but which may also generate social and economic costs that exceed the expected benefits.

It is important for regulators to consider involving other sectors, especially industry and agriculture, in these discussions. **Incorporating regulatory impact assessments**

(RIAs) before proposing restrictions on AI personalization, and **integrating productivity and economic efficiency data** into regulatory debates, are among the practical recommendations that emerge from this study, which also highlights the importance of using national empirical evidence as a reference in public consultations on AI.

For the private sector, the results reinforce that personalized AI is a driver of productivity and social legitimacy. Companies that use it transparently, responsibly, and in alignment with the Brazilian context tend to capture gains in efficiency, reputation, and more favorable regulation. On the other hand, ignoring the public debate on personal data, AI, and personalization may generate reputational risks, reactive regulation, and loss of international competitiveness.

It is important for companies across different sectors to participate actively in the debate on digital regulation, engaging in public consultations and sectoral coalitions that advocate for evidence-based policies, and treating **AI governance** as part of their business strategy, not as an isolated technical issue.

4.3. Integration between Economics and Regulation

Although Brazil has had more than a decade of robust discussions on data protection in the regulatory landscape, few economic studies have been conducted in this field — which creates a false impression of tension between economic evidence and the regulatory narrative.

These are not conflicting issues: **they are two legitimate ways of understanding technological progress.** While economics looks at efficiency and the expansion of production and national income, among other factors, regulation starts from uncertainty and the need for protection in the face of the unknown. In the case of AI, this difference becomes even more pronounced, especially when productivity gains are immediate and measurable, while the risks — such as discrimination and reduced freedom of choice — are diffuse and long-term. Treating these two dimensions as incompatible impoverishes the debate.

The quantitative results of this study, by suggesting that restrictions on AI personalization could reduce Brazil's GDP by 1.6%—compared with a scenario in which personalization is widely adopted—do not mean that regulation should be discarded, but rather **that it must be calibrated.** Effective public policy is not the one that merely eliminates risk, **but the one that preserves room for regulatory learning**—adjusting rules as empirical evidence accumulates. In this sense, the integration between economics and regulation requires a new type of institutional dialogue, which may **point toward a path of maturation in the Brazilian AI debate.**

By recognizing that economic gains and regulatory caution do not cancel each other out, but rather reinforce one another, the country can move toward **a governance model that uses economic evidence as a tool for social protection,** not as a counterpoint. Regulation informed by productivity and competitiveness data does not weaken individual rights; on the contrary, **it strengthens their sustainability** by ensuring that public policies can be financed, tested, and improved within a dynamic economy.

5. Conclusion

This study provides an unprecedented contribution by quantifying the macroeconomic impact of the personalization of Artificial Intelligence systems. By presenting the impacts on the Brazilian economy resulting from a ban on personalization (GDP 1.6% lower compared with a scenario of widespread personalization), the results offer a concrete empirical basis for a debate that, until now, has been conducted without robust empirical grounding.

This evidence is not intended to close the discussion, but to qualify it, introducing data that help quantify the economic cost of different regulatory choices. More than a measurement exercise, the study proposes a methodological shift: **understanding AI not merely as a technology, but as a driver of productivity that cuts across multiple sectors.**

We believe that the findings can encourage **a more informed, evidence-based public debate**, promoting public policies that **reconcile development and data protection** as parts of the same agenda.

6. Guidance for Future Studies

Based on the results and discussions of this work, as well as its methodological limitations, we highlight the following directions for future studies that may continue and improve this research:

i. **Empirical studies on social and cognitive impacts.** Suggested controlled experiments and surveys to measure the effects of personalization on attention, well-being, and behavior;

ii. **Distributional analyses.** Exploration of how the impacts of personalization (or its absence) affect employment, inequality, and innovation across different sectors and social groups.

iii. International benchmarking. Comparative mapping of how different jurisdictions regulate different types of personalization, highlighting best practices and shortcomings that can inform the Brazilian debate.

iv. **Sectoral Models of Personalized AI.** Develop econometric studies specific to each sector (such as agriculture, energy, and financial services) to identify variations in productivity gains and regulatory sensitivity to AI personalization.

v. **Experimental AI Regulation.** Test regulatory sandbox models for the personalization of AI systems, allowing empirical measurement of impacts, risks, and benefits before the adoption of general rules.

vi. **Trust, Transparency, and Social Acceptance.** Conduct empirical research with users and consumers to understand how perceptions of transparency and control affect the acceptance of AI personalization.

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Appendix: Impact ranking in the sectors

	RANKING: IMPACTO NOS SETORES	dVA
1º	Manufacture of tobacco products	-1,913
2º	Oil refining and coking plants	-1,897
3º	Slaughtering and meat products, including dairy and fish products	-1,886
4º	Manufacture of biofuels	-1,883
5º	Sugar manufacturing and refining	-1,873
6º	Agriculture, including agricultural support and post-harvest activities	-1,871
7º	Other food products	-1,856
8º	Livestock production, including livestock support activities	-1,849
9º	Oil and gas extraction, including support activities	-1,821
10º	Electric power, natural gas, and other utilities	-1,813
11º	Manufacture of organic and inorganic chemicals, resins, and elastomers	-1,811
12º	Forestry production; fishing and aquaculture	-1,781
13º	Iron ore extraction, including processing and agglomeration	-1,775
14º	Extraction of non-ferrous metallic minerals, including processing	-1,772
15º	Manufacture of pesticides, disinfectants, paints, and various chemicals	-1,767
16º	Manufacture of cleaning products, cosmetics/perfumes, and personal hygiene items	-1,764
17º	Non-ferrous metal metallurgy and metal casting	-1,763
18º	Manufacture of beverages	-1,759
19º	Manufacture of automobiles, trucks, and buses, except parts	-1,734
20º	Production of pig iron/ferralloys, steelmaking, and seamless steel tubes	-1,732

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	RANKING: IMPACTO NOS SETORES	dVA
21º	Land transport	-1,720
22º	Manufacture of pulp, paper, and paper products	-1,718
23º	Extraction of mineral coal and non-metallic minerals	-1,717
24º	Manufacture of rubber products and plastic materials	-1,711
25º	Water transport	-1,709
26º	Manufacture of non-metallic mineral products	-1,701
27º	Manufacture of electrical machinery and equipment	-1,695
28º	Manufacture of metal products, except machinery and equipment	-1,694
29º	Construction	-1,686
30º	Manufacture of parts and accessories for motor vehicles	-1,682
31º	Maintenance, repair, and installation of machinery and equipment	-1,678
32º	Public education	-1,677
33º	Public healthcare	-1,677
34º	Public administration, defense, and social security	-1,677
35º	Manufacture of wood products	-1,671
36º	Manufacture of textile products	-1,669
37º	Manufacture of footwear and leather goods	-1,669
38º	Manufacture of other transport equipment, except motor vehicles	-1,665
39º	Food services	-1,662
40º	Manufacture of computer equipment, electronic and optical products	-1,661
41º	Real estate activities	-1,661
42º	Telecommunications	-1,655
43º	Air transport	-1,655

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	RANKING: IMPACTO NOS SETORES	dVA
44º	Other professional, scientific, and technical activities	-1,644
45º	Television, radio, film, and sound/image recording and editing activities	-1,640
46º	Legal, accounting, consulting, and corporate headquarters activities	-1,639
47º	Non-real-estate rentals and intellectual property asset management	-1,637
48º	Manufacture of mechanical machinery and equipment	-1,627
49º	Surveillance, security, and investigation activities	-1,626
50º	Storage, transport support activities, and postal services	-1,625
51º	Manufacture of pharmaceutical and pharmaceutical-chemical products	-1,624
52º	Manufacture of furniture and miscellaneous industrial products	-1,615
53º	Water, sewage, and waste management	-1,613
54º	Architectural, engineering, testing/technical analysis, and R&D services	-1,609
55º	Printing and reproduction of recordings	-1,597
56º	Associative organizations and other personal services	-1,587
57º	Manufacture of clothing articles and accessories	-1,584
58º	Accommodation	-1,572
59º	Wholesale and retail trade	-1,564
60º	Artistic, creative, and performance activities	-1,562
61º	Other administrative activities and support services	-1,561
62º	Financial intermediation, insurance, and supplementary pension services	-1,554
63º	Publishing and publishing integrated with printing	-1,549
64º	Private healthcare	-1,495
65º	Systems development and other information services	-1,477
66º	Private education	-1,368

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Reglab Methodology Appendix

REGLAB SPECIAL FORMATS

AUTHORSHIP: João Ricardo Costa Filho e Pedro Henrique Ramos

Title	The Economic Dimension of Personalization: Measuring the Impact of Personalized Artificial Intelligence on the Brazilian GDP
Research Question	What is the macroeconomic impact of banning the personalization of artificial intelligence tools on the Brazilian economy?
Methodology Summary	Calculation of sectoral exposure to Artificial Intelligence; general equilibrium control model calibrated for the Brazilian economy. Projection of the baseline scenario for Brazil's GDP over the next 10 years. Calculation of the present value of the impact of the aggregate productivity loss.
Data Collection	***Desk research using secondary data, as follows:*** • Exposure index by activity (Felton, Raj, and Seamans, 2021). • Exposure index by occupation (Cazzaniga et al., 2024). • U.S. occupational categories (SOC). • International occupational categories (ISCO). • Brazilian occupational categories (CBO). • Microdata from the National Household Sample Survey (PNAD) by IBGE – last quarter of 2024. • 2024 GDP: R$ 11.7 trillion (Source: IBGE, SCNT). • Real GDP growth rates projected in the Focus Report (BCB, Sep 12, 2025).

Data Analysis	The model used in this study is based on the work of **Delalibera (2024)**. This model was chosen because it incorporates important characteristics of the Brazilian economy that more generic models do not. First, it includes a **productive public sector**, recognizing that the Brazilian state is not only a regulator or consumer but also a producer in areas such as energy and services. Second, the model incorporates a **complex tax system,** taking into account the different tax rates applied to different sectors and products. Third, the model recognizes that many markets do not operate under perfect competition, but under **imperfect competition**, where firms have market power and can set prices. This feature, inspired by the works of **Baqaee and Farhi (2020)** and **Acemoglu and Azar (2020)**, is important because it affects how productivity shocks translate into changes in prices and quantities.
	The number and definition of sectors derive from the **input–output matrix** calculated by the Brazilian Institute of Geography and Statistics (IBGE). In addition, the following references were used for data analysis and calculations:
	• Exposure index by activity (Felton, Raj, and Seamans, 2021).
	• Exposure index by occupation (Cazzaniga et al., 2024).
	Weight of each occupation in the Brazilian economy:
	  • **1º passo:** Harmonization of occupational categories: U.S. occupational category (SOC) → International occupational category (ISCO) → Brazilian occupational category (CBO).
	  • **Step 2:** National Household Sample Survey (PNAD) microdata from IBGE – last quarter of 2024:
	• Individual weights, each associated with an occupation (CBO) linked to a CNAE;
	• Calculation of the weight of each occupation in each CNAE;
	• Sum of (Exposure by occupation × weight of each occupation in each CNAE) = sector-level average exposure.
	• Construction of the Reference Scenario:

Data Analysis

- 2024 GDP: R$ 11.7 trillion (Source: IBGE, SCNT).
- Real GDP growth rates projected in the Focus Report (BCB, Sept 12, 2025).
  - For 2029 and 2030, the 2028 rate was repeated.
  - Discount rate: Selic rate projected in the Focus Report.
  - For 2029 and 2030, the 2028 projections were repeated.
  - Inflation rate (IPCA) projected in the Focus Report. For 2029 and 2030, the 2028 projections were repeated.

It is important to highlight that occupations not present in the **International Standard Classification of Occupations (ISCO)** were excluded, and the remaining occupations were reweighted.

In constructing the reference scenario, the 2024 GDP and the real growth rates projected by the median of respondents in the Central Bank of Brazil's Focus Report (as of October 10, 2025) were used. For the years from 2029 onward, the same growth rate projected for 2028 (2%) was applied. Similarly, Selic and IPCA projections were used to calculate the intertemporal discount factor, that is, the factor applied to compute the present value of potential GDP losses resulting from the non-personalization scenario in future years.

Bias Mitigation Procedures

To mitigate biases, we used empirical analysis references that are widely established in the literature. In addition, the methodological approach was discussed and evaluated internally on two occasions so that suggestions and critiques could be incorporated into the work before the analysis was carried out.

Other procedures adopted include:

Double Validation in Critical Stages: for the 'Analysis and Comments' section, both authors independently reviewed the text. In cases of disagreement, a third person was brought in to arbitrate and reach a consensus.

Methodological Record-Keeping and Transparency: we maintained detailed records of all file versions and research steps, preserving the history and enabling more systematic review.

Other procedures adopted include:

Dependência de Fontes de Acesso Aberto: O estudo dependeu significativamente de pesquisas realizadas em bancos de dados e revistas acadêmicas de acesso aberto. A dependência dessas fontes pode restringir a abrangência da análise, considerando que materiais relevantes presentes em bases de acesso restrito ou especializadas podem não ter sido consideradas, o que pode comprometer a completude e a profundidade do texto apresentado.

Software Use

Software	Use in research
Suíte MS Office	Editing of text, spreadsheets, and charts
Suíte Adobe C	Layout design and finalization of charts and illustrations
Google Gemini	Grammatical review (spelling, grammar, synonym search), language refinement, and adjustments to pre-drafted sections
R	Harmonization of different datasets and estimation of sectoral exposure to AI.
Matlab	Simulation of the general equilibrium model.
ChatGPT	Assistance in programming the simulations.
Manus	Development of the writing.

Ethical Guidelines	This research was funded by Facebook Serviços Online do Brasil Ltda ('Meta'). To ensure the integrity of this work, the authors developed, conducted, and analyzed the study independently, without any contribution or interference from the company, which also did not influence or interfere with the interpretation of the results. The authors maintain full professional independence and responsibility for the content and conclusions of this work. **Respect for 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, their use was conducted responsibly and ethically, with the sole purpose of academic research. **Non-discrimination and Respect for Diversity:** The research was conducted in a manner that respects diversity and avoids any form of discrimination.