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Artificial intelligence: where does Brazil stand in global scientific production and what are the main technical determinants of adoption by Brazilian companies

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Abstract

Purpose – Artificial Intelligence (AI) has the potential to significantly increase long-term economic productivity. Although available evidence indicates that the use of AI in major business processes is still quite limited, countries such as China and the USA are at the forefront of technology development. For developing economies not to lag behind, it is essential to be prepared through innovation-friendly public policies, which can be more efficiently formulated with an understanding of the factors influencing the adoption of AI by firms. This research paper aims to contribute to this objective by providing a brief characterization of the scientific literature on AI in Brazil and worldwide, and by evaluating the determinants of AI adoption by Brazilian companies.

Design/methodology/approach – We use a bibliometric tool developed by the OECD to characterize AI research, and parametric modeling – logit, in RStudio, to evaluate the determinants of AI adoption in Brazilian firms.

Findings – The results that emerge from the analysis point out that Brazil's scientific production on AI is much lower than that of the leading experts, but the rates of AI adoption by companies are in line with those of European countries. As the main technical determinants of AI adoption in Brazilian companies, the use of the internet of things (IoT), cloud computing, big data analysis and the existence of a digital security policy stand out, which reinforces the need to harmonize the different government strategies related to digital transformation in Brazil.

Originality/value – As far as we are concerned, this is the first attempt to conduct this kind of analysis in Brazil, with Information and Communications Technology (ICT) Enterprises Survey 2021 data.

Keywords Artificial intelligence, 4.0 technologies, Digital maturity

Paper type Research paper

1. Introduction

The fourth industrial revolution has, as one of its purposes, the stimulation of digital manufacturing through heightened digitization and interconnectedness among products, value chains and business models, alongside supporting research endeavors. It is characterized by

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interconnected machines, intelligent products and systems and integrated solutions, enabling intelligent production units that monitor and govern physical devices (European Commission, 2017; Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014; Tortorella & Fettermann, 2018). Embedded within a context of digitization – i.e. the continual convergence of the real and virtual realms as the primary driver of innovation and transformation across all economic sectors (Kagermann, 2015), it encompasses enabling technologies that, when combined with emerging technologies, can profoundly enhance intricate industrial ecosystems (Xu, Xu, & Li, 2018).

Artificial intelligence (AI), arguably the most prominent technology in the present landscape, has engendered promises of productivity gains, enhancements in well-being and even the potential to become a substantial tool in addressing major challenges such as global warming. Although there are persisting issues and challenges related to reliability, privacy and security, among others, the technology has demonstrated growing popularity, to the extent that the OECD AI Policy Observatory has already documented over 800 policy initiatives across 69 jurisdictions (Caira & Perset, 2023).

AI is intertwined with a series of other emerging technologies, such as robotics, autonomous vehicles, virtual or augmented reality and Industry 4.0, among others. In manufacturing, specifically, AI possesses the potential to revolutionize all processes, spanning from design to manufacturing and assembly, employee training, predictive and preventive maintenance, inventory management, distribution and product sales. Within the supply chain, AI can be harnessed for warehouse management, logistics and supplier relationships (Ezell & Lazar, 2022).

The integration of these novel technologies into current work systems, including the processes they are capable of underpinning, remains an open question (Kolberg, Knobloch, & Zühlke, 2017) so despite auspicious prospects the boundaries of this phenomenon remain considerably diffuse (Lima & Gomes, 2020). The initial phase of this new cycle allows the coexistence of existing technologies rooted in the industrial era with cutting-edge technologies. This combination highlights the absence of a clearly defined technological transformation, underscoring the extreme importance for developing economies to prepare through public policies that support innovation (Arbix, Salerno, Zancul, Amaral, & Lins, 2017).

In Brazil, certain authors have raised concerns about the country's delay in keeping pace with the fourth industrial revolution – citing a lack of governmental initiatives and low prioritization of innovation in terms of public policies, among other factors. However, in recent years, significant projects have been undertaken with the aim of fostering technological evolution at the national level, with notable examples being the Brazilian Digital Transformation Strategy (E-Digital) and the Brazilian Artificial Intelligence Strategy (EBIA).

As the escalating relevance that technologies like AI assumes in facilitating productivity growth and integrating developing countries into the international arena, it is of utmost importance to comprehend how Brazil compares to leading AI-developing countries from diverse perspectives. Two indicators aiding in this comprehension pertain to the production of scientific papers and the adoption of the technology by companies. Hence, to achieve these objectives, this work employs bibliometric analysis to contribute to the characterization of the scientific literature on AI both in Brazil and globally, and parametric modeling – the logit model, utilizing data from the 2021 ICT Enterprises Survey, to estimate the key determinants of AI adoption in Brazil.

The article is structured into four sections, in addition to this introduction. Section 2 presents a literature review on AI within the context of public policies and levels of adoption within companies. Section 3 outlines the methodology, encompassing bibliometric analysis and binary choice models – logit. Section 4 presents the results and discussion, and finally, the concluding remarks are presented in Section 5.

2. Literature review

2.1 Technology adoption

In Brazil, the discourse surrounding new technologies has aimed to identify, beyond potential impacts on industrial productivity, other opportunities for the structural transformation of the economy – the country is exposed to advancements that have already materialized in other countries, given its low capacity for technological innovation and dependency on commodities (Arbix *et al.*, 2017). One concern is linked to Brazil's ability to keep pace with the ongoing industrial revolution and consequently seize the potential rewards of the early adopters.

A couple of surveys conducted with companies have aided in delineating the evolution of new technologies in Brazil, indicating low awareness, especially among small businesses, as a substantial obstacle to utilization. High implementation costs are highlighted as the primary internal barrier, along with a lack of skilled workers as the primary external challenge. General findings have also confirmed the relatively low maturity in Brazil's digitalization process (CNI, 2016, 2022). Additionally (Ruiz, Torraca, Britto, & Ferraz, 2023), indicated among the organizational factors and market conditions with significant influence on the trajectory of new technologies: the size of the company – the larger, the higher the probability of adopting more advanced digital technologies, and being embedded in a digital intensive sector – competitive pressure stimulates firms to advance in the adoption of digital technologies.

Despite the structural challenges underscored in the literature, significant initiatives have been undertaken in Brazil in recent years to support the nation's digital transformation, particularly in the realm of AI. In this context, the Brazilian Digital Transformation Strategy (E-Digital), the Brazilian Artificial Intelligence Strategy (EBIA), and more recently, the Brazilian Plan for Artificial Intelligence (PBIA) stand out.

The E-Digital is divided into two major thematic axes – Enabling Axes and Digital Transformation Axes [1]. While enabling axes form the foundation for digital transformation, digital transformation axes encompass strategies for digitally transforming governmental and economic activities. Within this framework, AI is frequently cited in the digital transformation axis known as "Data-driven Economy." AI is one of the technologies enabling business model enhancement and technological innovation to address the burgeoning production of data, which is increasingly essential for economic activities. AI is also integral to other strategic actions for the 2022–2026 quadrennium, including the promotion of R&D through government technology procurement. Equally important, the strategy addresses cybersecurity concerns and the regulation of critical technologies, particularly AI, as significant challenges to overcome.

In 2021, the federal government formulated the EBIA to guide Brazilian state actions toward developing initiatives capable of propelling research, innovation and the creation of AI solutions in various aspects. The document established nine thematic axes, characterized as the pillars of the strategy [2], in addition to providing a diagnosis of the current state of AI worldwide and in Brazil. Finally, the document highlighted the challenges to be addressed and proposed a set of strategic actions.

In July 2024, the Brazilian government proposed the PBIA, with an estimated investment of R$ 23 billion, more than half of which is allocated to business innovation, aimed at structuring a robust AI value chain. The plan is divided into five pillars: infrastructure and development; diffusion, training, and capacity building; improvement of public services; business innovation; and support for the regulatory and governance process. The main objectives include positioning the country as one of the global AI leaders while generating jobs and fostering innovation.

Regarding AI, the Organization for Economic Co-operation and Development (OECD) defines an AI system as machine-based, capable of influencing the environment by producing an output (predictions, recommendations or decisions) for a given set of objectives. It utilizes machine and/or human data and inputs to (1) perceive real and/or virtual environments; (2) abstract these perceptions into models through automated analysis (e.g. machine learning) or manually and (3) employ inference models to formulate output options. AI systems are designed to operate at various levels of autonomy. Examples include machine learning models, deep learning models, natural language processing (NLP) and computer vision (Ezell & Lazar, 2022).

The anticipation surrounding the promising future of new AI applications continues to grow, but empirical studies detailing their extent of utilization by companies are still relatively scarce, particularly concerning peer-reviewed scientific articles. In Brazil, IBM (2022) indicated that between March and April of 2022, 41% of companies in Brazil were actively implementing AI in their businesses [3], compared to a global rate of 35%. Additionally, a survey by Deloitte in 2023 found that 70% of surveyed companies plan to invest in AI, with 20% already using AI resources in their daily operations [4].

Kubota and Lins (2022) employed the ICT Enterprises Survey to compare Brazil and Europe regarding technology adoption. Brazil had 13% of its companies utilizing some form of AI, a higher level than most European countries – Denmark leads in Europe, with 24% of its companies declaring the use of some form of AI technology. Analyzing the characteristics of AI adoption, Brazil stood out with a higher number of companies using AI for workflow automation, followed by image recognition and processing, when compared to Europe. For other usage types, there was no significant difference between Brazilian and European companies.

The innovation survey conducted by the Brazilian Institute of Geography and Statistics investigated the adoption of advanced technologies of a sample representative of 8,134 [5] extractive and transformation industries with 100 or more employees. The percentage of adoption of the technologies are as follows: big data analysis (23.4%), cloud computing (73.6%), AI (16.9%), internet of things (IoT, 48.6%), addictive manufacturing (19.2%) and robotics (27.7%) (IBGE, 2023).

A comparative analysis of AI adoption in 10 countries – Belgium, Denmark, France, Germany, Ireland, Israel, Italy, Japan, South Korea and Switzerland – revealed certain stylized facts. Adoption is more pronounced in larger firms, newer firms, and in the ICT and professional services sectors. Proficiency in ICT and training, digital capabilities and digital infrastructure were significantly related to AI usage. Moreover, there were indications of a selection bias toward more digital and competitive firms – and thus, more productive firms – regarding AI adoption. If this trend persists, it may widen the productivity gap between more and less productive firms (Calvino & Fontanelli, 2022).

Regarding challenges to AI adoption by companies, a study from the OECD showed that even in the US, European Union and Japan, technology usage is relatively low. Factors such as lack of readiness for digitalization (e.g. lack of digitized information), concerns about AI costs, uncertainty about return on investment and concerns about access to qualified labor were cited as hindrances. In the European context, the main internal challenges encountered were (1) difficulty in hiring people with the necessary skills, (2) adoption costs and (3) operational process adaptation costs. External challenges include (1) lack of public financing, (2) legal liability for potential damages and (3) data standardization (Ezell & Lazar, 2022).

Another OECD study identified similar challenges, in addition to including other obstacles. Lack of AI skills, uncertainty about return on investment, difficulties in explaining AI predictions or prescriptions ("black box"), the need for business model changes, regulatory and ethical complexity, among others, were cited (OCDE, 2022).

2.2 Digital maturity of firms

Digital maturity models can play a pivotal role as a theoretical foundation in the investigation and characterization of new technology adoption within firms, such as AI, underscoring their significance in guiding technological integration. According to De Carolis, Macchi, Negri, and Terzi (2017), maturity frameworks facilitate the development of a comprehensive strategy ensuring the harmonization of organizational processes with targeted maturity benchmarks. This approach enables organizations to discern their maturity status and benchmark against their industry counterparts and also to pinpoint specific areas necessitating enhancement. Consequently, this process lays the groundwork for the formulation of a strategic roadmap.

A model of distinguished qualification designed to facilitate comprehension of digital technology adoption was put forth by Schuh, Anderl, Dumitrescu, and Krüger (2020), articulating six stages intricately associated with the processes of digitalization, as outlined in Table A1 in the Appendix. Stages 1 and 2 pertain to basic digitalization: digitizing data, integrating various company systems, and, for industrial firms, connecting key production equipment to an integrated management system. In stage 3, firms can monitor real-time business activities, from the factory floor to the supply chain and the usage of digital products and services by customers. In stage 4, the use of technologies enables the company to understand why things are happening. For instance, manufacturers can use AI to analyze the root cause of component failures – Big Data is commonly used at this stage. In stage 5, firms are poised for what will happen, such as predicting machine failures. Finally, in stage 6, autonomous machines are capable of detecting and even correcting their errors.

A similar manufacturing architecture of four layers was proposed by Lu and Weng (2018): sensor, integration, intelligent and response. The sensor layer monitors localized physical and environmental data. Integration collects the data from the previous layer and transmits it to a data management center. The intelligent layer analyses integrated information and makes predictions using data analytics and algorithms. Finally, the response layer develops different applications and services on top of the previous three layers.

Rosa and Kubota (2024) employed Multiple Correspondence Analysis (MCA) to provide an introductory characterization of AI usage among Brazilian companies. By incorporating three other digital technologies (big data, IoT and cloud processing) into the analysis, along with firm size and digital security policies, the authors suggest, through graphical analysis, an apparent dependence of firms on the use of various technologies to advance in the digital transformation process. While MCA allows for the exploration of associations within categorical datasets in a visually intuitive manner, it offers limited depth and does not address causal effects or predictive analysis [6].

Battistoni, Gitto, Murgia, and Campisi (2023) conducted a survey with 421 manufacturing small and medium-sized enterprises (SMEs) from Tuscany, Italy. The authors used Partial Least Squares Structural Equation Modelling and Necessity Condition Analysis to investigate how much each layer of digital technologies proposed by Lu and Weng (2018) contributes to the implementation degree of the technologies associated with the upper layer, and also if the technologies of the lower layers enable the implementation of the technologies of the upper layers.

Results indicate that digitalization is mainly enabled by sensor technologies, which provide the needed input for the proper functioning of the technologies associated with the integration, intelligence and response layers. Integration seems to play a major enabler role for intelligent and response technologies, while intelligent technologies seem to be still weakly combined with response technologies (Battistoni *et al.*, 2023).

Frank, Dalenogare, and Ayala (2019) surveyed 92 manufacturing firms in Brazil to discern various adoption patterns of Industry 4.0 technologies. The authors clustered the firms in three clusters, according to the adoption of the following technologies: the IoT, cloud, big data and analytics. The findings underscored that 44 firms were characterized as low adopters, 33 as moderate adopters and only 15 as advanced adopters.

The literature attempts to analyze in various ways how the adoption of AI by companies is related to other digital technologies, many of which align directly with digital maturity models. For instance, Sestino, Prete, Piper, and Guido (2020) argued that the growing popularity of IoT and big data has made them central to companies' digitalization strategies, enabling data-driven decision-making processes to foster greater efficiency.

In a broader spectrum, Merhi and Harfouche (2024) assessed twelve enablers of AI adoption in production systems, which were then divided using the Technology, Organization and Environment (TOE) framework. The authors concluded that technology, as a category, takes precedence over the other pillars – i.e. decision-makers should focus on this category when implementing AI.

For the food industry, Hassoun *et al.* (2023) performed a literature review to highlight the key roles of several technologies – among them robots, the IoT, big data and AI – as enablers of Industry 4.0 in the sector. Misra *et al.* (2022) emphasized the disruptive role of IoT, big data and AI in the success of modern agriculture and the food industry. Meanwhile Aceto, Persico, and Pescapé (2020) discussed the positive impacts on healthcare of adopting and integrating technologies such as IoT, big data, cloud computing and AI, which has the capability to analyze vast amounts of data and thus automate learning and decision-making processes.

Firouzi, Farahani, and Marinšek (2022) analyzed how the interaction of IoT, cloud computing and edge computing influences AI applications. According to the authors, although the IoT and cloud computing landscapes are distinct and have evolved independently, their elements are often complementary, leading to a convergence of these technologies in recent years. In this context, the interaction between edge and cloud computing has proven essential in expanding the possibilities of IoT applications, particularly those reliant on AI.

According to the review presented, the determinants for the adoption of AI are considered as part of two broad categories – organizational and technical – based on the data available from the 2021 ICT Enterprises Survey. The first category includes attributes such as company size, region and industry sector, while the second relates to other technologies, ranging from connectivity issues to advanced technologies.

3. Methodology

The following subsections provide detailed information on the utilized database and the procedures for bibliometric analysis and parametric modeling.

3.1 Database

To assess the determinants of AI adoption by Brazilian companies, the empirical study utilized microdata from the 2021 ICT Enterprises Survey. According to Comitê Gestor da Internet no Brasil (2022), out of the planned sample of 7,000 companies, 4,064 interviews were conducted between August 2021 and April 2022 [7]. Table 1 presents details about the variables used in the study:

The variable related to AI (H9_AGREG) encompasses various applications. If at least one of them is used, the variable assumes a value of 1.

(1) Text Mining (H9_A): Does this company employ AI technologies for: Text mining and analysis of written language?;

(2) Speech recognition (H9_B): Does this company employ AI technologies for: Speech recognition, converting spoken language into machine-readable format?;

(3) Natural language processing (H9_C): Does this company employ AI technologies for: NLP for written or spoken language?;

(4) Image recognition (H9_D): Does this company employ AI technologies for: Image recognition and processing, identifying objects or individuals?;

(5) Machine learning (H9_E): Does this company employ AI technologies for: Machine learning, such as deep learning, for data prediction and analysis?;

(6) Automation of workflow processes (H9_F): Does this company employ AI technologies for: Automation of workflow processes?;

(7) Physical movement of machines through autonomous decisions (H9_G): Does this company employ AI technologies for: Physical movement of machines through autonomous decisions, such as robots, vehicles and autonomous drones?.

Table 1. Description of variables

Variable	Description
Region	Represents the regional division of Brazil according to IBGE criteria, in macro-regions: (1) North; (2) Northeast; (3) Southeast; (4) South; (5) Midwest
Size	Represents the division by small, medium, and large companies based on the number of employees: (2) 10–49 employees; (3) 50–249 employees; and (4) 250 employees or more
Markets – CNAE 2.0	Represents the classification of companies in sections denoted as C, F, G, H, I, J, L + M + N, R + S: (1) Manufacturing; (2) Construction; (3) Trade; repair of motor vehicles, personal and household goods; (4) Transportation, Storage, and Postal Services; (5) Accommodation and Food Services; (6) Information and Communication; (7) Real Estate Activities + Professional, Scientific, and Technical Activities + Administrative and Support Services; (8) Arts, Culture, Sports and Recreation + Other Service Activities
Fiber optics	In the last 12 months, did the company use fiber optic connection?
ERP	In the last 12 months, did the company use Enterprise Resource Planning (ERP) applications?
Cloud processing	In the last 12 months, did the company pay for cloud processing capacity?
Big data	In the last 12 months, did the company perform big data analyses?
Industrial robots	In the last 12 months, did the company use industrial robots?
Service robots	In the last 12 months, did the company use service robots?
3D printing	In the last 12 months, did the company use 3D printing?
Internet of things	Does your company use IoT devices?
Digital security policy	Does your company have a digital security policy?
AI (H9_AGREG)	Artificial Intelligence for at least one application

Note(s): It is worth noting that, since the 2017 edition, the information disclosed is based on that available in the registry rather than what the respondent declared at the time of the interview, as was the case until the 2015 edition (Comitê Gestor da Internet no Brasil, 2022)
Source(s): Own elaboration based on Comitê Gestor da Internet no Brasil (2022)

For all variables in Table 1 (except for region, size and Classificação Nacional de Atividades Econômicas (CNAE, i.e. National Classification of Economic Activities, the Brazilian system for classifying economic activities)) and from H9_A to H9_G, the response possibilities included: 0 = “No”; 1 = “Yes”; 97 = “Do not know”; 98 = “No response”; and 99 = “Not applicable”. Responses with numbers 97, 98 and 99 were replaced with 0 since lack of knowledge and no response should imply non-usage.

A challenge in evaluating the determinants of AI adoption through the 2021 ICT Enterprises Survey is that module H (New Technologies) questions were exclusively directed to companies with an IT department. According to the survey report, this was done based on the preexisting knowledge of the greater complexity of such companies compared to others. Consequently, from the initial sample of 4,064 respondents, only 2,328 who reported having an IT department were retained. No further data modifications were necessary.

3.2 Bibliometric analysis

The exponential growth in the number of documents over the last decades has made bibliometric analysis a powerful tool for investigating subjects of interest and identifying future research areas (Bonilla, Merigó, & Torres-Abad, 2015). According to Donthu, Kumar, Mukherjee, Pandey, and Lim (2021, p. 285):

> [. . .] bibliometric analysis is useful for deciphering and mapping the cumulative scientific knowledge and evolutionary nuances of well-established fields by making sense of large volumes of unstructured data in rigorous ways. Therefore, bibliometric studies that are well done can build firm foundations for advancing a field in novel and meaningful ways—it enables and empowers scholars to (1) gain a one-stop overview, (2) identify knowledge gaps, (3) derive novel ideas for investigation, and (4) position their intended contributions to the field.

Bibliometric methodology is based on the application of quantitative techniques to scientific literature. While performance analysis considers the individual contributions of various research components, such as authors, institutions and countries, science mapping examines the relationships between research components, addressing intellectual interactions and structural connections among them.

In this paper, we choose to conduct a bibliometric analysis using a prominent tool called OECD.AI, developed by the OECD exclusively for the domain of AI [8], which is capable of providing bibliometric indicators through publications from OpenAlex and Scopus, in addition to offering detailed insights into research activities across a broad array of countries.

The OECD.AI platform diverges from the conventional method of conducting bibliometric studies, which typically relies on manually searching specific terms on platforms like Web of Science and Scopus, followed by the use of analysis tools such as the VOSViewer software, the bibliometrix package of RStudio, among others. The advantage of OECD.AI is that it relies on machine learning and semantic inference, among other techniques, to explore academic information and thus characterize scientific literature in AI. It also employs NLP to index information by article type, author, publication date, field of study, publication venue and institution. In the context of bibliometric analysis, the platform offers both performance analysis and science mapping.

For the analysis of global scientific production and Brazil's integration within this context, three indicators are utilized: (1) the ratio between the number of AI publications and GDP per capita by country and region, annually; (2) the collaboration between Brazil and its principal partner countries in the publication of articles on AI; and (3) the research areas in which researchers with institutional affiliations in Brazil have most frequently published articles on AI.

The identification of scientific articles on AI is conducted through the use of keywords associated with AI in the Scopus database, as detailed in de Kleijn, Siebert, and Huggett (2019). For the quantitative measurement of articles by country, a count is employed that applies equal weights to each co-author of the publication – i.e. a paper with three co-authors from different countries will have its count as one-third of a publication for each country. The GDP per capita measure, in turn, is defined as the gross domestic product divided by the mid-year population – the databases used are from the World Bank and the OECD.

Country collaboration is facilitated through the allocation of each article to the respective countries of the authors according to their institutional affiliations. To qualify as international collaboration, co-authorship must be between institutions in different countries. Moreover, to avoid double counting in the collaboration between countries, articles written by authors from more than one institution in the same country – in collaboration with a foreign institution – are counted only as one collaboration for that country.

Regarding the research areas in the Scopus database, they refer to the specific categories or disciplines under which research and scientific literature are classified. Based on the content of the document, such as the topics addressed, the disciplines cited, and the keywords used, the research areas are not mutually exclusive, meaning a single article can be classified under more than one theme.

3.3 Parametric modeling

In this study, a logit model is used to test the determinants of AI adoption in Brazilian companies; the dependent variable is binary, representing the adoption or non-adoption of AI.

According to Gujarati and Porter (2009), the logistic distribution function is given by:

$$P_i = \frac{e^{Z_i}}{1 + e^{Z_i}} \tag{1}$$

where $Z_i = \beta_1 + \beta_2 X_i$, X_i is the set of explanatory variables, β_i is the set of coefficients and P_i is the probability of the studied event occurring, ranging from 0 to 1.

Given that $1 - P_i = \frac{1}{1+e^{Z_i}}$, it is possible to write $\frac{P_i}{1-P_i} = e^{Z_i}$, where $\frac{P_i}{1-P_i}$ is the ratio of the occurrence and non-occurrence of the event. The logit model, L, will be:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_1 + \beta_2 X_i \tag{2}$$

The probability of the event occurrence is not directly observable, but the dependent variable Y_i is and assumes 1 if the technology is adopted and 0 otherwise. Thus, considering Y_i as a Bernoulli random variable, it's possible to write $\Pr(Y_i = 1) = P_i$ e $\Pr(Y_i = 0) = (1-P_i)$. Assuming a random sample with n observations, the joint probability of observing the n values of the dependent variable can be described by the linearized likelihood function (LLF):

$$LLF = \ln f(Y_1, Y_2, \ldots, Y_n) = \sum_1^n Y_i(\beta_1 + \beta_2 X_i) - \sum_1^n \ln\left(1 + e^{(\beta_1+\beta_2 X_i)}\right) \tag{3}$$

where $\beta_1 + \beta_2 X_i = \ln\left(\frac{P_i}{1-P_i}\right)$. The parameter estimates are obtained by maximizing the likelihood function, but the coefficients of the logit model do not have a direct interpretation as marginal effects when estimated, unlike linear regression models. The marginal effect in the logit model will be given by $\beta_j P_i(1 - P_i)$, where β_j is the coefficient of the partial regression of the j-th regressor. The coefficients reflect the change in the probability of event occurrence associated with changes in X_i, while keeping other variables constant $\left(\frac{\partial P_i}{\partial X_i}\right)$.

The estimated econometric model will take the form:

$$AI_i = \ln\left(\frac{P_i}{1-P_i}\right) = \alpha + \beta X_i + u_i \tag{4}$$

where AI is the dependent variable; β is the vector of coefficients; and X comprises the categorical explanatory variables: fiber optics, ERP, cloud, big data, industrial robots, service robots, 3D printing, IoT, digital security, size, region and CNAE.

The specification validity test of the model is performed according to the "linktest" command in Stata software, which is based on Pregibon (1979). In this test, the adequacy of the model is assessed by the non-significance of additional regressors. This is done using the linear and squared predicted values (_hat and _hatsq, respectively). While the former should be statistically significant – it is the predicted value from the model, the latter should not have much predictive power.

Regarding the goodness of fit, Pearson χ^2 statistic operates by dividing the estimated outcome probabilities into ordered groups and comparing the concordance between the expected outcome frequencies in these groups and the actual observed frequencies. The non-significant result suggests that the estimated and observed frequencies are aligned and a statistically significant result signals a lack of fit.

4. Results and discussion

4.1 Scientific literature in AI – bibliometric analysis

We start with a broader bibliometric analysis to determine the countries that stand out as major producers of scientific documents on AI worldwide, including an assessment of where Brazil positions itself within this global context. Figure A1 in Appendix presents the number of scientific publications in AI, accumulated from 2010 to 2022, compared with the per capita GDP by country and region. It can be observed that China and the United States lead in the number of publications. These two countries are followed by G7 members: India, Austria, South Korea and Spain. Brazil appears in the following group, alongside the Netherlands, Russia, Indonesia and Ireland. This representation can be classified as a form of performance analysis, thus identifying the key components – countries – in the research field.

The rivalry between the two leading AI publishers is one of the expressions of a larger rivalry. According to Rikap and Lundvall (2021), there is a complex interaction between the corporate and national innovation systems of both countries, which could even be interpreted as a dispute for global technological supremacy.

To partially restrict the analysis and better characterize Brazil's position in the international research network on AI, the platform also enables an analysis of collaboration between Brazil and other countries in scientific works in the field. As shown in Figure A2 in the Appendix, the prominent group of countries that Brazil collaborates with includes the European Union, followed by the United States, United Kingdom and Canada. While China has the highest number of publications, as shown in Figure A1 in the Appendix, Sino-Brazilian collaboration in AI is still in its early stages. Among Latin American countries, Colombia and Chile stand out as the only representatives.

In terms of the main research areas publishing scientific works on AI in Brazil, as shown in Figure A3 in the Appendix, three of them have consistently ranked among the top five since the beginning of the series: (1) AI, (2) computer science applications and (3) software. The field of AI maintained the lead until 2020 when it was surpassed by the field of computer science applications. In the field of engineering, Electrical and Electronic Engineering ranks 3rd, and Control and Systems ranks 8th in 2022. For comparison, fields such as Medicine, Biological and Agricultural Sciences, and Social Sciences have minimal representation compared to the publications related to computing/systems. The OECD.AI platform utilizes Scopus database data for constructing this graph.

4.2 AI adoption

Tables A2 and A3 in Appendix illustrate the sample compositions for binary and categorical variables, respectively.

When it comes to the utilization of AI technology, the percentage of companies responding positively is 33%. On the other hand, digital security policy exhibits higher percentages, nearing 77%. Among the technologies with lower adoption rates are service robots (3.39%), 3D printing (5.58%) and industrial robots (5.84%). Among the most adopted technologies from module H are IoT (34.19%), AI (33.38%) and big data (17.31%).

The dependent variable pertains to AI adoption by the company, and its determinants are estimated using a logit model in the Stata software. According to Lange, Montagnier, and Phillips (2023, p. 18):

> to compare the speed at which new technologies diffuse, one should compare neither absolute changes in adoption rates nor relative changes. Instead, one should account for the level of adoption in making comparisons. This can be done using logistic growth models[...].

Table 2 presents the results of the logit model with robust standard errors which ensures that the variance–covariance matrix of the estimators is robust to non-constant error variance. The estimates refer to odds ratios – i.e. the odds of adopting a certain technology by a specific group divided by the odds of adoption by another group. As per Lange *et al.* (2023), absolute or relative differences are not good measures for determining the importance of certain characteristics in a company – e.g. size, on the adoption of a technology. It is preferable to compare odds ratios, which, under reasonable diffusion process considerations, will not depend on the adoption level in different segments.

Since all regressors are binary, one category is omitted from each group of variables with multiple categories. Within each group, odds ratios are based on the omitted category in the results presentation. Drawing upon Núñez, Fuentes, and Monroy (2021) and Vittinghoff,

Table 2. Logit model of AI adoption determinants

	Unweighted TI companies
Technologies	
Fiber optics	1.00
	(0.01)
ERP	1.00
	(0.00)
Cloud	1.71***
	(0.17)
Big data	2.12***
	(0.27)
Industrial robots	1.66*
	(0.36)
Service robots	1.31
	(0.35)
3D printing	1.70*
	(0.36)
IoT	2.58***
	(0.26)
Digital security	1.60***
	(0.21)
Region	
Northeast	0.90
	(0.18)
Southeast	0.97
	(0.17)
South	0.86
	(0.16)
Central-West	1.06
	(0.22)
Size (employees)	
50–249	0.99
	(0.11)
250 or more	1.28
	(0.17)
Market	
Construction	1.17
	(0.24)
Trade	0.98
	(0.15)
Transport	1.40
	(0.27)
Accommodation and food	0.62*
	(0.14)
Information and communication	1.31
	(0.24)
Real estate, scientific and admin.	1.34
	(0.26)
Arts, culture, sports	1.14
	(0.26)
No of companies	2,328
Pearson (GOF)	1371.47 (Prob > $\chi^2 = 0.13$)

Note(s): ***, ** and * significant at 0.1, 1 and 5%, respectively
Source(s): Authors' elaboration with TIC Companies 2021 data

Glidden, Shiboski, and McCulloch (2012), the model is valid according to the specification test and the goodness of fit measure, as shown in Table 2 and Table A4 in the Appendix.

The overall correctly classified rate of the model was 72.12%, supporting its robustness in handling typical data variabilities in industrial economics studies. For industry standards, model outputs exhibiting accuracy levels exceeding 70% are generally considered acceptable and provide substantial empirical value. Complimentary statistics include the specificity rate, which stands at 89.36%, suggesting that the model is highly effective at correctly identifying true negatives. On the other hand, the model achieves a sensitivity of 37.71%, indicating a moderate ability to detect true positive cases.

As an alternative, a probit model was estimated with the same set of variables. As expected, the results were similar in terms of statistical significance and coefficient signs. In descending order of magnitude for statistically significant coefficients, IoT, big data, cloud computing and digital security policy stood out. Nevertheless, the logit model was chosen due to its advantage in interpreting results using odds ratios, as well as its greater popularity in empirical studies.

From the estimation of the logit model, particular emphasis is placed on the relevance of four variables that positively influence the adoption of AI in Brazilian companies: the presence of a digital security policy, the use of cloud computing, the use of big data and the use of IoT. In terms of odds ratios, the highest magnitude is seen in the utilization of IoT – companies using this technology are 2.58 times more likely to adopt AI compared to companies that do not use it. For the use of big data, cloud computing and the presence of a digital security policy, the values are 2.12, 1.71 and 1.6, respectively.

The results seem to confirm the perspective of digital maturity presented in the literature review section. The adoption of more advanced stages of digitization, such as autonomous models, requires the existence of devices like sensors for the "Visualization" stage: understanding what is happening in the firm. It also requires the use of big data for the "Understanding" stage: comprehending why something is happening in the company. In many cases, these technologies necessitate cloud computing infrastructure for storing and processing large volumes of data. The use of industrial robots and 3D printing was significant only at the 5% significance level. On the other hand, connectivity quality, measured by the presence of fiber optic connectivity, the use of service robots and the use of integrated management systems (ERP) did not show significant correlations with AI adoption.

This interpretation bears similarities to the findings of CNI (2022), in which sectors with a high technological intensity not only stand out for their diversified use of digital technologies but also illustrate the concept of pioneering in the incorporation of still-emerging innovations in the industrial scenario, marking crucial milestones in this climb toward digital maturity. Contrasting with this advancement, the observation that the majority of companies are at the initial stages of digitalization, with a limited adoption of digital technologies, underscores the need for progressive development that paves the way for subsequent innovations. This progression is fundamental for the full realization of AI, which relies on the synergy between different technologies, emphasizing the interdependence among them as one of the cornerstones of digital transformation.

The outcomes also give support to the findings of Battistoni *et al.* (2023), according to which the adoption of digital technologies can be classified into hierarchical layers that are responsible for the collection, integration, processing and utilization of organizational data. Within this framework, the implementation of more advanced technologies such as AI cannot be analyzed in isolation; that is, it will depend on underlying layers capable of enabling and enhancing its utilization. Therefore, IoT, cloud computing and big data would operate at the sensor, integration and intelligence layers, which together may enable AI solutions in the response layer.

These findings reinforce the results of other studies in the literature, according to which the integration of technologies like IoT and big data has become a cornerstone of digitalization strategies across various industries. The growing adoption of these technologies has empowered companies to implement data-driven decision-making processes (Sestino *et al.*, 2020), and has led to improvements through the automation of learning and decision-making processes, enabled by the analysis of large datasets (Aceto *et al.*, 2020). Moreover, the complementarity of IoT and cloud computing, as highlighted by Firouzi *et al.* (2022), further enhances the potential of AI applications, offering more scalable and efficient solutions across sectors.

Considering the magnitude of the odds ratios, the adoption of AI by companies has been primarily driven by the IoT, highlighting the relevance of the National IoT Plan (PIoT) – launched in 2019 – to the current AI landscape. Although the PIoT was well-structured, as it stemmed from a collaboration between BNDES, the Ministry of Science, Technology, Innovations and Communications (MCTIC), and the McKinsey/CPqD/Pereira Neto Macedo Advogados consortium, its implementation faced significant setbacks due to the coronavirus disease 2019 (COVID-19) pandemic in 2020 [9]. One of the few tangible outcomes was the establishment of the 4.0 Chambers. The current surge of interest in AI presents an opportunity to revive and leverage the valuable initiatives from this plan that were not fully implemented at the time.

The presence of a digital security policy has also proven to be highly significant. With growing frequency, issues related to digital security are not confined to the business realm. As individuals, organizations and governments have become reliant on connectivity-based devices and technologies – which can offer opportunities to enhance people's lives and well-being (Lange *et al.*, 2023), they have also become more susceptible to cyber threats. In this context, the ability to protect against such attacks has become a significant concern (WEF - World Economic Forum, 2023).

Within the business sphere, discussions about the increasingly important role of a digital security policy in structuring digitization have occupied extensive space in the literature. However, many doubts persist in terms of awareness and the best way to implement strategies. According to WEF - World Economic Forum and Accenture (2023, p. 4), based on a survey of 117 respondents from 32 countries and 22 industries:

> business leaders are more aware of their organizations' cyber issues than they were a year ago. They are also more willing to address those risks. Nonetheless, cyber leaders still struggle to clearly articulate the risk that cyber issues pose to their organizations in a language that their business counterparts fully understand and can act upon. As a result, agreeing on how best to address cyber risk remains a challenge for organizational leaders.

The results from Table 2 also demonstrate that larger firms are more likely to adopt AI when compared to smaller ones, although statistical significance is lacking. Preliminary models developed within the scope of this study – without considering digital technologies – indicated that the variable related to firm size was statistically significant. According to CNI (2022) and Ruiz *et al.* (2023), a company's capability to adopt new technologies is influenced by its size, with larger companies demonstrating a more comprehensive adherence to digital technologies, suggesting that the climb in the hierarchy of digital maturity is also a journey of technological expansion proportional to the scale and resources of the company. Therefore, it is possible to suggest that the capacity to implement IoT, big data, cloud computing and a digital security policy is related to the size of the company.

OECD studies corroborate the dominance of large firms in adopting digital technologies on the global stage. According to Calvino and Fontanelli (2022, p. 5), "AI is more widely used across large firms. Scale advantages may be relevantly related to more considerable endowments of (or capabilities to use) intangibles and other complementary assets needed to fully leverage the potential of AI." Other reasons may include economies of scale, larger amounts of data to leverage AI applications and fewer financial constraints.

This behavior can also be explained by complementary assets that are significantly related to the use of AI, including skills and ICT training, enterprise-level digital capabilities and digital infrastructure. As stated by Calvino and Fontanelli (2022, p. 9), "(M)ore general skills and innovative activities, which may also increase firm absorptive capacity, appear also positively linked to AI use."

5. Concluding remarks

This study aimed to briefly characterize some aspects of the scientific literature on AI in Brazil and assess the technical determinants of AI adoption by Brazilian companies. For this purpose, a bibliometric analysis was conducted using the OECD.AI platform, followed by the estimation of a logit model as an econometric analysis.

Bibliometrics pointed to Brazil's difficulties in emerging as a prominent figure in the development of scientific works in the field of AI. Apart from China and the USA, which vie for leadership in global scientific production, developed countries also demonstrate some capacity to secure subsequent positions. In terms of collaboration with other countries, a potential strategy to accelerate national scientific production could involve greater engagement with China, the global leader in AI-related scientific literature production, which does not rank among Brazil's primary partners, despite the partnership of both countries within the BRICS framework.

The parametric analysis, by highlighting four variables as the most important for positively influencing the adoption of AI by Brazilian companies (adoption of IoT, cloud computing, big data and digital security policy), corroborates the scientific literature which states that autonomous decision models are at the apex of a hierarchy of technologies. Models like AI necessitate technologies that support them, such as sensors (enabling managers to "observe" what is happening within the company), infrastructure to safely store large volumes of data and techniques for analyzing this data (to understand what is happening within the firm). Sensors are associated with IoT, storage and analytical techniques are associated with cloud and big data, while safety is associated with digital security policy.

From a public policy standpoint, there is observed leadership from the legislative power in the discussion on the matter, with various regulations being discussed both in the Chamber of Deputies and the Federal Senate. Within the Executive branch, the discussion on updating the Brazilian Strategy for AI has recently started, and after being launched in July 2024, the PBIA is awaiting validation from the President of the Republic to come into effect (Conselho Nacional de Ciência e Tecnologia and Ministério da Ciência, Tecnologia e Inovação, 2024).

Out of the proposed R$ 23 billion investments in PBIA, R$ 9.4 billion are for the Program AI for the challenges of Brazilian industry. The goal is to fund at least 500 AI industry projects until 2028. The origin of resources are funds from Plan More Production, managed by the Brazilian Development Bank (BNDES) and funded by FINEP (Funding Authority for Studies and Projects). This program is aligned with the industrial policy: New Industry Brazil (NIB) [10].

Another program mentioned in PBIA is Brazil More Productive. This program was inspired by the Journey of Digital Transformation (JDT) – targeting micro, small and medium firms – developed by FIESP, CIESP, SENAI and SEBRAE. The philosophy of the JDT and, therefore, Brazil More Productive is very aligned with the results of this study: firms will not reach higher levels of excellence without the required managerial and technical foundations [11].

The results from the present paper reinforce the need to harmonize the different strategies and programs conducted on the national level (e-Digital, National IoT Plan, EBIA, PBIA), which can make the path toward AI adoption smoother for businesses. In other words, it is not possible to analyze AI in isolation from other related technologies.

The present study was exclusively based on information from the ICT Enterprises 2021 dataset. Future studies could benefit from cross-referencing with other databases, such as the Annual Social Information Report (Rais).

Notes

1. Data-driven economy; A universe of interconnected devices; Emerging business models; and Citizenship and governance.
2. The nine pillars of EBIA are: (1) Legislation, Regulation, and Ethical Use; (2) AI Governance; (3) International Aspects; (4) Qualifications for a Digital Future; (5) Workforce and Training; (6) Research, Development, Innovation, and Entrepreneurship; (7) Application in Productive Sectors; (8) Application in the Public Sector; and (9) Public Security.
3. See https://www.ibm.com/blogs/ibm-comunica/estudo-ibm-41-das-empresas-no-brasil-ja-implementaram-ativamente-inteligencia-artificial-em-seus-negocios/. Access in jul 22, 2023.
4. See https://invest.mcti.gov.br/blog/em-2023-7-em-cada-10-empresas-brasileiras-investirao-em-inteligencia-artificial/. Access in jul 22, 2023.
5. Of a total of 9,586 firms, 8,134 used advanced technologies.
6. By contrast, the present paper employs a logit model and considers eight digital technologies (fiber optics, ERP, cloud processing, big data, industrial robots, service robots, 3D Printing and IoT) as potential technical determinants of AI adoption. This framework provides a significantly more robust and nuanced examination, which includes variable control, effect estimation, and statistical inference – e.g. the impact of explanatory variables on the probability of AI adoption with their respective confidence intervals – as well as predictive capabilities, i.e. estimating the probability of AI adoption based on new data.
7. The companies were contacted through the computer-assisted telephone interview technique. In all surveyed companies, an attempt was made to interview the person responsible for the area of informatics, information technology, computer network management or equivalent area. In companies that reported having 250 occupied individuals or more at the time of the interview, the strategy was to interview a second professional, preferably the manager of the accounting or financial area. Each company in the sample was assigned a basic sample weight, obtained by the ratio between the number of companies existing in the stratum and the sample size in the corresponding final stratum. There was also non-response correction for cases in which responses were not obtained from all selected individuals.
8. Available at https://oecd.ai/en/data?selectedArea=ai-research.
9. The authors of the study interviewed Guilherme Correa and Karina Vidal, of Ministério da Ciência, Tecnologia e Inovações – MCTI for an Industry 4.0 study.
10. See: https://agenciagov.ebc.com.br/noticias/202408/nova-industria-brasil-ganha-mais-credito-e-novos-parceiros. Access in September 29, 2024.
11. See: https://jornadadigital.sp.senai.br/#etapas. Access on September 22, 2024. The authors of the study interviewed Mr. Bruno Sousa, of SENAI São Paulo for an Industry 4.0 study.

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Supplementary material
The supplementary material for this article can be found online.

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