Patterns of international collaboration in Artificial Intelligence:
a bibliometric analysis, 2010-2021

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Resumo

Este artigo investiga o fluxo global de conhecimento em Inteligência Artificial, um domínio com significativo potencial disruptivo. Analisando dados de coautoria internacional de artigos científicos, exploramos as interações no setor através de duas linhas: i) Sistemas Setoriais de Inovação, oferecendo percepções sobre especificidades do setor e o potencial de catch-up de países retardatários; e ii) Análise de Rede, ilustrando seu comportamento e suas implicações para a economia e pesquisa em inovação. Utilizando a Web of Science, identificamos 1.097.821 artigos de IA em todo o mundo, dos quais 235.932 (21%) representam um fluxo de conhecimento internacional.

Palavras-chave: Inteligência Artificial; Sistemas de Inovação; Bibliometria; Co-autoria.

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Abstract

This article delves into the global knowledge flow within Artificial Intelligence, a domain with significant disruptive potential. By analyzing international co-authorship data from scientific articles, we explore the interaction dynamics within the AI sector through the lens of two key literatures: i) Sectoral Systems of Innovation, offering insights into sector-specific nuances and latecomer countries' catch-up potential; and ii) Network analysis, illuminating the network's behavior and its implications for the field of economics and innovation research. Using the Web of Science database, we identified 1,097,821 AI articles worldwide, from which 235,932 (21%) represent an international knowledge flow.

Keywords: Artificial Intelligence; Innovation Systems; Bibliometrics; Co-authorship.

1 Introduction

Since the term AI was coined in 1956, research in the field has experienced periods of both excitement and decline (RUSSELL; NORVIG, 2021). Currently, various authors are pointing to AI's influence on the emergence of a new stage in the global economy. In this context, new definitions have arisen, such as the Fourth Industrial Revolution (SCHWAB, 2016), Platform Capitalism (SRNICEK, 2017), Surveillance Capitalism (ZUBOFF, 2019), and the Digital Age (UNCTAD, 2019). The ongoing transformations also raise new concerns about the advent of AI, including those related to race (NOBLE, 2018), employment (ACEMOGLU; RESTREPO, 2019), and privacy (TIROLE, 2021).

The impact of AI on inequality among countries has been increasingly discussed in the literature (CRAWFORD, 2021), often identifying the emergence of new forms of colonialism based on data and digital technologies (COULDRY; MEJIAS, 2019; KWET, 2019). The control of digital capabilities by large multinational corporations presents challenges for middle and low-income countries that lack the firms and resources required for this competition (ANDREONI; ROBERTS, 2022). For the Global South, it is essential to adopt strategies to absorb knowledge to catch-up with industrial leaders (FREEMAN, 1995; LEE, 2019).

Understanding global knowledge flows is key to informing strategies for the Global South. Our work aims to analyze the knowledge flows through international collaboration in AI-related academic articles. We define international knowledge flow as articles co-authored with at least one member from a foreign university. Adopting a keyword strategy to filter the AI articles in the Web of Science database (LIU; SHAPIRA; YUE, 2021), we identified a total of 1,097,821 AI articles worldwide, from which 235,932 (21%) represent an international knowledge flow. This number is considerably higher than in other works, providing a comprehensive view of the sector. Our focus on global knowledge flows enriches bibliometric literature and sheds light on the Global South's role in global innovation dynamics.

We follow Li et al. (2021) recommendation to combine Sectoral Innovation Systems literature with network approaches. The former provides essential conceptual developments and case studies for understanding industrial sectors, while the latter elucidates the connections among actors in innovation systems. Our analysis of international collaboration networks sheds light on the AI sector's interactions and fosters the integration of these two bodies of literature. Additionally, we evaluate the evolution of network patterns over time.

Our findings show China as the foremost nation in AI research publications, with the US in second place. The representation of the Global South is limited, though countries like China, India, and Iran are notable exceptions. Our analysis also identifies certain patterns within the BRICS+ group. Moreover, the knowledge flow network exhibits traits of complex systems and has demonstrated a stable pattern throughout the years.

Apart from the introduction and conclusion, this paper comprises four main sections. The first section conducts a literature review, focusing on the Sectoral Innovation System literature and the network dynamics of AI. The second section details the data and methods for tracking knowledge flows. The third and fourth sections present the results and their discussion, respectively.

2 Literature review

2.1 Innovation Systems

When looking at the determinants of innovation in countries of the Global South, it's essential to emphasize the need to internalize knowledge generated in other countries, thereby creating the capacity for endogenous innovation (FREEMAN, 1995). According to Freeman (1995, p. 18), a country will only be successful in absorbing foreign technology if it adopts institutional changes that strengthen autonomous technological capacity and consider the interplay between technical and organizational innovations. The diversity of factors that interconnect to absorb knowledge and drive innovation leads us to the approach of National Innovation Systems (FREEMAN, 1987; LUNDVALL, 1992; NELSON, 1993).

We can define innovation systems as "all important economic, social, political, organizational, institutional, and other factors that influence the development, diffusion, and use of innovations" (EDQUIST, 2004). This approach helps us understand the innovation process beyond firm boundaries and the pursuit of profitability, emphasizing a broad interplay of factors that generate and benefit from innovative activity. Similarly, Soete; Verspagen; Ter Weel (2010) argue that the central idea of this approach is that "innovation at the aggregate level is, in fact, the result of an interactive process that involves many actors at the micro level, and that next to market forces, many of these interactions are governed by non-market institutions" (p. 1163). Understanding innovation as a product of a system allows us to go beyond research and development (R&D) expenditures as the sole source of innovation, highlighting aspects such as university-industry connections, user-producer relationships, and individual learning processes. Moreover, this approach draws attention to the possibility of systemic failures as opposed to market failures, as, given the importance of non-market institutions, poor innovation performance may be due to coordination failures among different parts of the system (SOETE; VERSPAGEN; TER WEEL, 2010, p. 1168).

The boundaries of innovation systems are commonly defined in national, regional, or sectoral terms. More recently, the literature has pointed to the emergence of global innovation systems, a phenomenon resulting from the high degree of global connectivity among actors and institutions engaged in innovative activities (BINZ; TRUFFER, 2017). Britto; Ribeiro; Albuquerque (2021) argues that the global innovation system constitutes a new layer, which does not nullify national, regional, and sectoral spheres. According to the authors, this new layer represents an opportunity for the Global South, as it strengthens the flow of knowledge between countries (BRITTO; RIBEIRO; ALBUQUERQUE, 2021). The concept of a new layer is consistent with the view of industrial capitalism as a complex system. This new layer can establish a new hierarchy and change the level of complexity of the system as a whole.

Our research aims to align more closely with the Sectoral Innovation Systems approach (MALERBA, 2002), which has seen significant progress in AI industry studies (LI et al., 2021). This initiative builds on foundational work in industrial dynamics, incorporating concepts such as technological regimes (NELSON; WINTER, 1982), general purpose technologies (BRESNAHAN, 2010), and technological catch-up (LEE; MALERBA, 2017). The research on AI’s transformative potential is growing, with some studies underscoring its impact (COCKBURN; HENDERSON; STERN, 2019; TRAJTENBERG, 2019), while others scrutinize its scope (LEE; LEE, 2021). Additionally, Jacobides; Brusoni & Candelon (2021) have contributed to integrating the AI industry within the evolutionary framework of industrial dynamics.

As argued by Li et Al. (2021), network research is a central component of the Sectoral Innovation Systems approach, yet it remains underexplored in the literature. This research focuses on the interplay among various actors in the system, providing an overview of the strengths and weaknesses of these connections, which are essential to the innovation activity. Recent studies have refined this approach, providing valuable insights to understand specific industries (TAALBI, 2020). Our study intends to enrich this body of work by examining the network of scientific advances in the AI sector.

Our research also engages with the Global Innovation Systems literature by addressing global knowledge flows. Prior research has explored these dynamics through scientific collaboration (RIBEIRO; BRITTO; ALBUQUERQUE, 2022; RIBEIRO et al., 2018), showing a growing activity in collaborative science and occasionally positing the emergence of a Global Innovation Systems (BRITTO; RIBEIRO; ALBUQUERQUE, 2021). Other works deal more specifically with AI, discussing actors' relations in the system (YU; LIANG; WU, 2021) and global innovation linkages (YU; LIANG; XUE, 2022).

2.2 Network analysis and AI

Our research converses with network approaches to science (WAGNER; LEYDESDORFF, 2005). In this sense, we can evaluate if our network of knowledge flows behaves as a complex system, in the sense established by Santa Fe Institute (FONTANA, 2010). Complex systems can be understood as systems composed of a multitude of smaller elementary entities that interact with each other (RIBEIRO, 2022). In these systems, the response to a disturbance (i.e., something that affects their behavior) is not equivalent to the initial disturbance, a characteristic known as non-linearity. Additionally, it is essential to note that different observation scales organize themselves differently, leading to distinct behaviors. This characteristic allows for the emergence of novel properties: more aggregated scales exhibit characteristics that are absent at less aggregated scales. Moreover, the phrase "more is different" encapsulates the idea that an increase in the number of elements results in more interactions and diverse forms of organization (ANDERSON, 1972).

Examples of complex systems include the sandpile model (ANDERSON, 2018) and the El Farol model (ARTHUR, 2010). The sandpile model describes a scenario where the constant addition of a new grain of sand to a pile results in avalanches occurring at different scales, thus affecting the entire system. This behavior can be associated with a scale-free system, defined as "one in which perturbations at all possible scales are equally close to dynamical instability" (ANDERSON, 2018). Understanding such scale-free networks requires working with characteristics like hierarchy and self-organization, which suggest the presence of complex systems (RIBEIRO et al., 2017)

On the other hand, the El Farol model depicts a "minority game" that does not follow a regular or random behavior pattern. In this model, patrons of a bar (let's say, El Farol bar in Santa Fe) prefer to avoid crowded situations. Consequently, they make decisions about whether to attend the bar based on their expectations of the occupancy of the establishment. Assuming the presence of rational expectations, when the forecast indicates that the bar will be too crowded, no individual will choose to attend, contradicting the original forecast. In contrast, when the forecast suggests that the bar will be empty, all patrons will choose to visit the establishment. The notable challenge here lies in the self-referential nature of expectations, where each individual's decision is based on the expectations of others' behavior. This leads to a cycle of contradiction, where predictions, due to their shared nature, often nullify each other. "As a theory of expectations formation, rational expectations fails here. The indeterminacy is also manifest in this case. Any attempt to deduce a reasonable theory of expectations that applies to all is quickly confounded" (ARTHUR, 2010, p. 161).

The study conducted by Ribeiro et al. (2017) is particularly significant as it identifies characteristics of complex systems within the capitalist economy. This conclusion implies that equilibrium models are not highly effective in understanding the dynamics of innovation and provides insights into the self-organization of networks in scientific and technological production.

Some studies specifically address AI within network analysis. For instance, bibliometric research has tracked AI's development over time (HO; WANG, 2020; LEI; LIU, 2019), but these often have a narrow AI scope, analyzing only about ten thousand papers—our study, however, has identified over a million articles. Other research explores AI applications in fields like finance (GOODELL et al., 2021), healthcare (TRAN et al., 2019) and education

(HINOJO-LUCENA et al., 2019). A key reference for our work is Liu; Shapira & Yue (2021), who introduces a novel methodology for tracking AI publications—a method we will discuss further in the following section. They also analyze general trends in AI publications, providing insights that will inform our analysis.

3 Data and methods

Our approach is based on a bibliometric search query to track AI related articles worldwide. Then, we analyze co-authorship patterns to identify knowledge flows. We collected data from the Web of Science, an extensive database on academic articles provided by the analytics company Clarivate.

A first question is how to properly filter AI publications. We rely on the work of Liu; Shapira & Yue (2021) to construct a lexical keyword-based query, carefully elaborated from high frequency keywords and Web of Science categories (Table 1). As shown by the authors, this approach offers a broad yet rigorous selection of articles, dialoguing with other similar approaches, some of them too narrow (GAO; HUANG; ZHANG, 2019; ZHOU et al., 2019), others too broad, capturing non-related articles (WIPO, 2019).

We considered international knowledge flow to be any article published in co-authorship with at least one member located at a university in another country. Different universities, even if located in the same country, are counted as a new interaction. Each article is assigned to the country where the first author's university is located, following a method usually used in pátent research, which avoids double counts. Thus, there is a difference between articles and interactions, since a country or university can have many interactions without being associated with the first author of the publication.

Our results provide insight into the international knowledge flow system in AI for scientific articles. Finally, we aim to assess whether this system behaves as a complex system and highlight potential implications of this characteristic.

Table 1 - Search approach for AI

No	Search strategy	Search terms
1	Core lexical query	TS =("Artificial Intelligen*" or "Neural Net*" or "Machine* Learning" or "Expert System$" or "Natural Language Processing" or "Deep Learning" or "Reinforcement Learning" or "Learning Algorithm$" or "*Supervised Learning" or "Intelligent Agent*")
2	Expanded lexical query 1	TS =(("Backpropagation Learning" or "Back-propagation Learning" or "Bp Learning") or ("Backpropa- gation Algorithm*" or "Back-propagation Algorithm*") or "Long Short-term Memory" or ((Pcnn$ not Pcnnt) or "Pulse Coupled Neural Net*") or "Perceptron$" or ("Neuro-evolution" or Neuroevolution) or "Liquid State Machine*" or "Deep Belief Net*" or ("Radial Basis Function Net*" or Rbfnn* or "Rbf Net*") or "Deep Net*" or Autoencoder* or "Committee Machine*" or "Training Algorithm$" or ("Backpropagation Net*" or "Back-propagation Net*" or "Bp Network*") or "Q learning" or "Con- volution* Net*" or "Actor-critic Algorithm$" or ("Feedforward Net*" or "Feed-Forward Net*") or "Hopfeld Net*" or Neocognitron* or Xgboost* or "Boltzmann Machine*" or "Activation Function$" or ("Neurodynamic Programming" or "Neuro dynamic Programming") or "Learning Model*" or (Neuro- computing or "Neuro-Computing") or "Temporal Diference Learning" or "Echo State* Net*")
3	Expanded lexical query 2	TS =("Transfer Learning" or "Gradient Boosting" or "Adversarial Learning" or "Feature Learning" or "Generative Adversarial Net*" or "Representation Learning" or ("Multiagent Learning" or "Multi-agent Learning") or "Reservoir Computing" or "Co-training" or ("Pac Learning" or "Probabl* Approximate* Correct Learning") or "Extreme Learning Machine*" or "Ensemble Learning" or "Machine* Intelli- gen*" or ("Neuro fuzzy" or Neurofuzzy) or "Lazy Learning" or ("Multi* instance Learning" or "Multi- instance Learning") or ("Multi* task Learning" or "Multitask Learning") or "Computation* Intelligen*" or "Neural Model*" or ("Multi* label Learning" or "Multilabel Learning") or "Similarity Learning" or "Statistical Relation* Learning" or "Support* Vector* Regression" or "Manifold Regulari?ation" or "Decision Forest*" or "Generali?ation Error*" or "Transductive Learning" or (Neurorobotic* or "Neuro-robotic*") or "Inductive Logic Programming" or "Natural Language Understanding" or (Ada- boost* or "Adaptive Boosting") or "Incremental Learning" or "Random Forest*" or "Metric Learning" or "Neural Gas" or "Grammatical Inference" or "Support* Vector* Machine*" or ("Multi* label Clas- sifcation" or "Multilabel Classifcation") or "Conditional Random Field*" or ("Multi* class Classifca- tion" or "Multiclass Classifcation") or "Mixture Of Expert*" or "Concept* Drift" or "Genetic Program- ming" or "String Kernel*" or ("Learning To Rank*" or "Machine-learned Ranking") or "Boosting Algorithm$" or "Robot* Learning" or "Relevance Vector* Machine*" or Connectionis* or ("Multi* Kernel$ Learning" or "Multikernel$ Learning") or "Graph Learning" or "Naive bayes*

		Classif*" or "Rule-based System$" or "Classifcation Algorithm*" or "Graph* Kernel*" or "Rule* induction" or "Manifold Learning" or "Label Propagation" or "Hypergraph* Learning" or "One class Classif*" or "Intelligent Algorithm*")
4	WoS category	WC =("Artificial Intelligence")
5	Total	#4 OR #3 OR #2 OR #1

Source: Liu; Shapira; Yue (2021).

4 Results

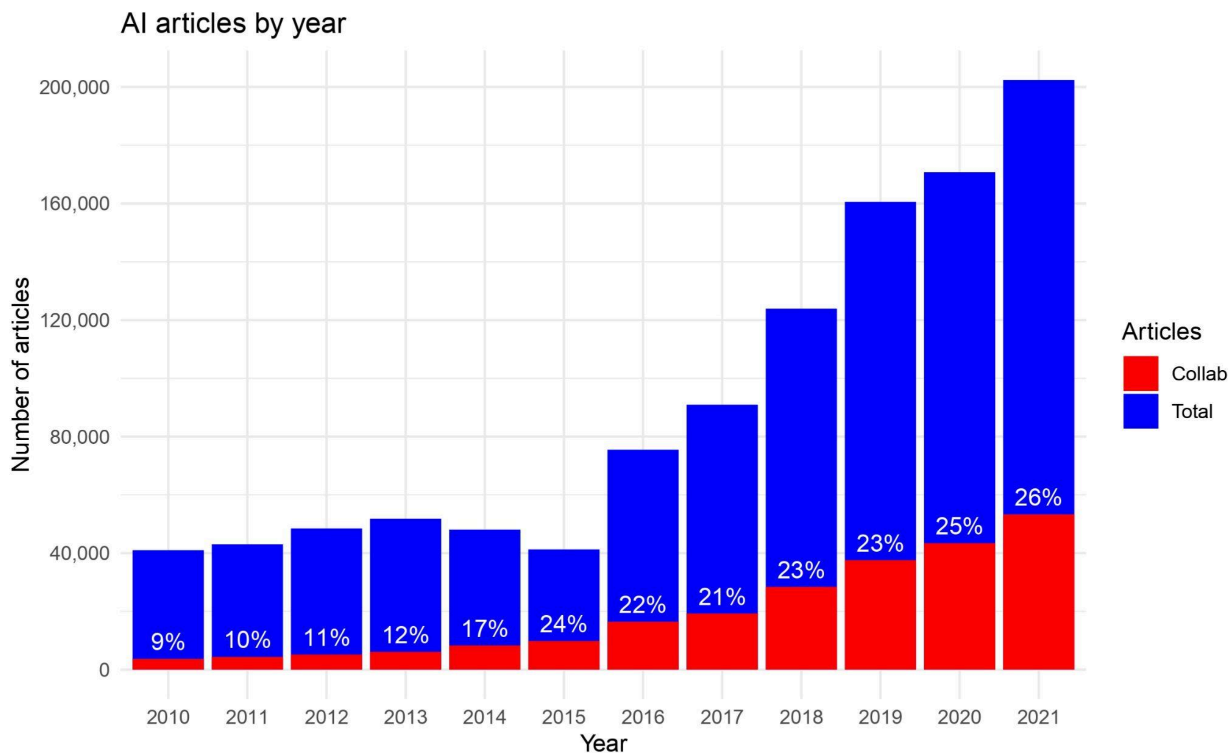
We identified a total of 1,097,821 AI articles worldwide between 2010 and 2021. Of this total, 235,932 (21%) resulted from at least one international collaboration, thereby constituting a knowledge flow.

The trajectory of collaborative AI articles has exhibited a consistent upward trend over the observed period, with a marked increase in both collaborative and overall publications beginning in 2015 (Figure 1). The total number of articles has seen a significant annual growth, escalating from 41,010 in 2010 to 202,418 in 2021, marking an almost fivefold increase in annual publications. Concurrently, the number of collaborative articles has experienced an even more pronounced rise, climbing from 3,696 (9% of the total) in 2010 to 53,297 (26%) in 2021. This represents a more than fourteenfold increase, indicating a trend towards more internationalized research.

Figure 2 presents the aggregate data for the entire period for the top 10 countries by the number of collaborative articles. China leads with the highest count of AI articles, totaling 296,750, of which 57,896 (20%) are internationally co-authored. The United States follows with 153,652 articles, 27,327 (18%) of which are international collaborations. Notably, half of these countries fall below the global average of 21% for collaborative articles, with India (11%) and Japan (13%) showing lower levels of international research collaboration, whereas Great Britain is highly internationalized, with 37% of its AI articles being co-authored.

Within the top ten nations for collaborative AI articles, the majority are high-income countries, with the US at the forefront. China and India, both middle-income countries and members of the BRICS group, also feature prominently. Utilizing the BRICS+ framework to assess the Global South's representation, we observe the following rankings: Iran in 11th place, Brazil 16th, Russia 30th, Egypt 36th, United Arab Emirates 44th, South Africa 48th, and Ethiopia 75th. In contrast, the G7 nations, except for Japan at 12th place, dominate the top 10, highlighting the disparity in research output between these groups.

Figure 1 - AI articles by year

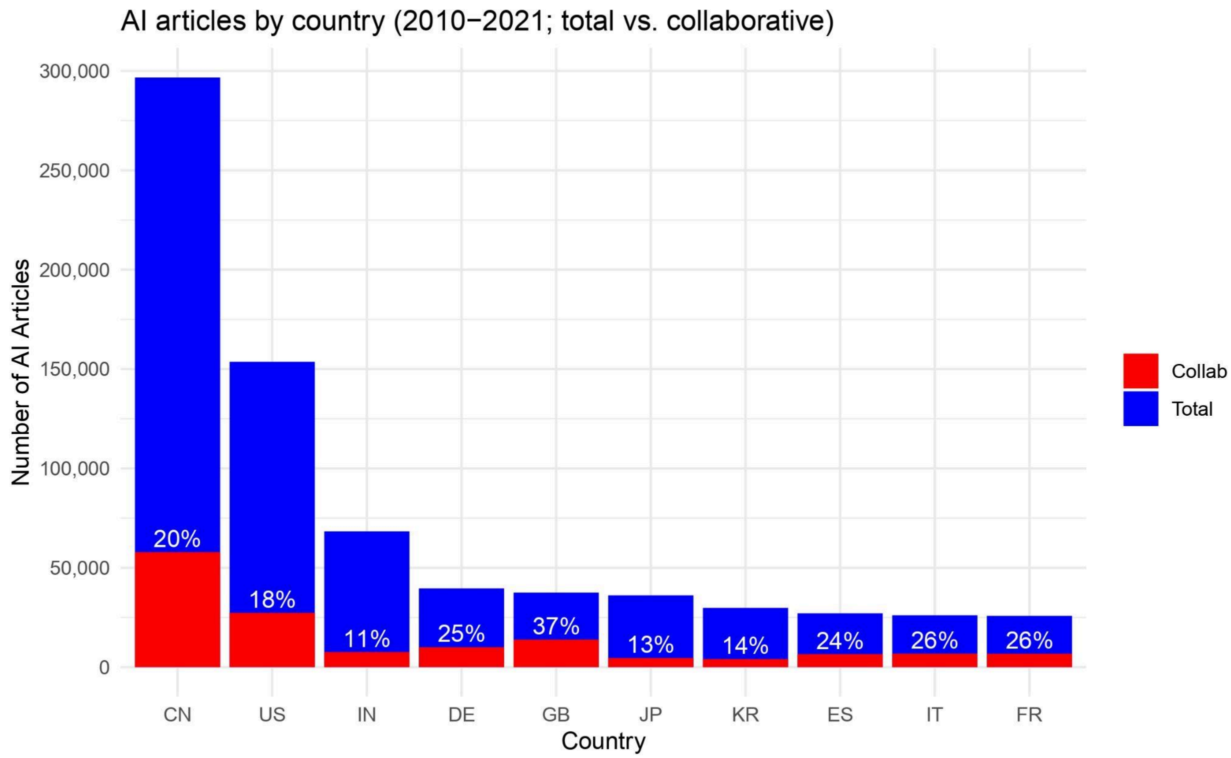


Source: our elaboration based on data from the Web of Science.

The comparison of AI collaborative article ratios between China and the US reveals that in 2010, they were nearly equivalent, with a ratio close to one (Figure 3). This ratio has significantly increased over the years, with China's numbers more than doubling those of the US by 2021. This trend suggests that China is outpacing the US, positioning itself as the predominant global leader in AI output. Aside from Germany, most other countries produce less than half the number of US publications. Notably, India's surpassing of Canada in 2020 prompts further investigation into India's research trajectory.

A closer examination of India's AI research reveals a consistent upward trajectory since 2010, with the country catching-up to major economies, despite their own significant advancements (Figure 4). In 2010, India produced 66 collaborative articles, ranking 14th. This number increased to 2,373 articles in 2021 alone, propelling India to 4th place for the year and 5th cumulatively, just behind Germany.

Figure 2- AI Articles by Country (Total vs. Collaborative)



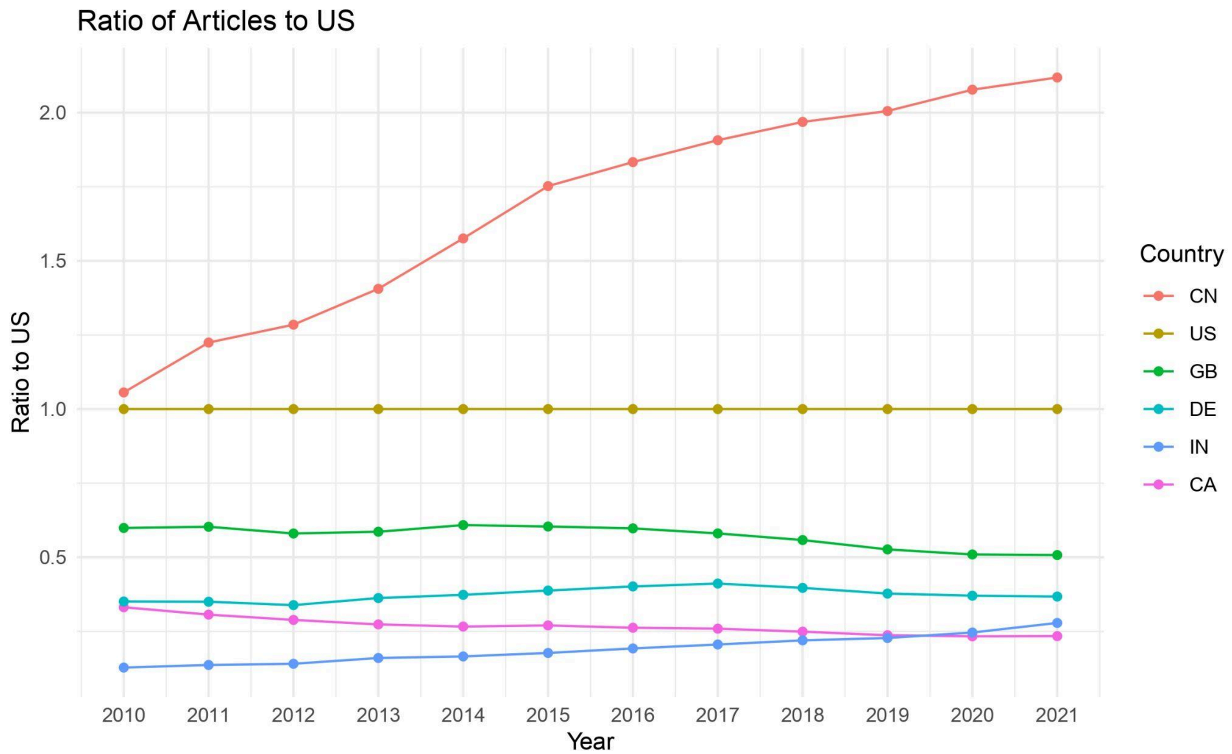
Source: our elaboration based on data from the Web of Science.

When analyzing the interactions between countries (Table 2), which accounts for all instances of participation in internationally co-authored articles—not exclusively as the first author and potentially including multiple interactions per article—we categorize a country as "China-inclined," "US-inclined," or "GB-inclined" based on their primary collaborator in terms of total interactions. This analysis reveals a distinct pattern from what was previously observed. The US is the principal collaborator for 100 of 187 countries (53%)[1], while Great Britain is the top collaborator for 24 countries (13%), and China for only 10 countries (5%), ranking below France, which leads for 19 countries (10%). Notably, all countries within the top 10 for total AI articles (Figure 2) are US-inclined. This trend is especially noteworthy for China, as it and the

[1] Note that for articles we have a total of 167 countries, while for interactions we have 187.

US are each other's main collaborators, highlighting the interconnectedness of their economies and research activities, despite escalating geopolitical tensions.

Figure 3 - Ratio of articles to US

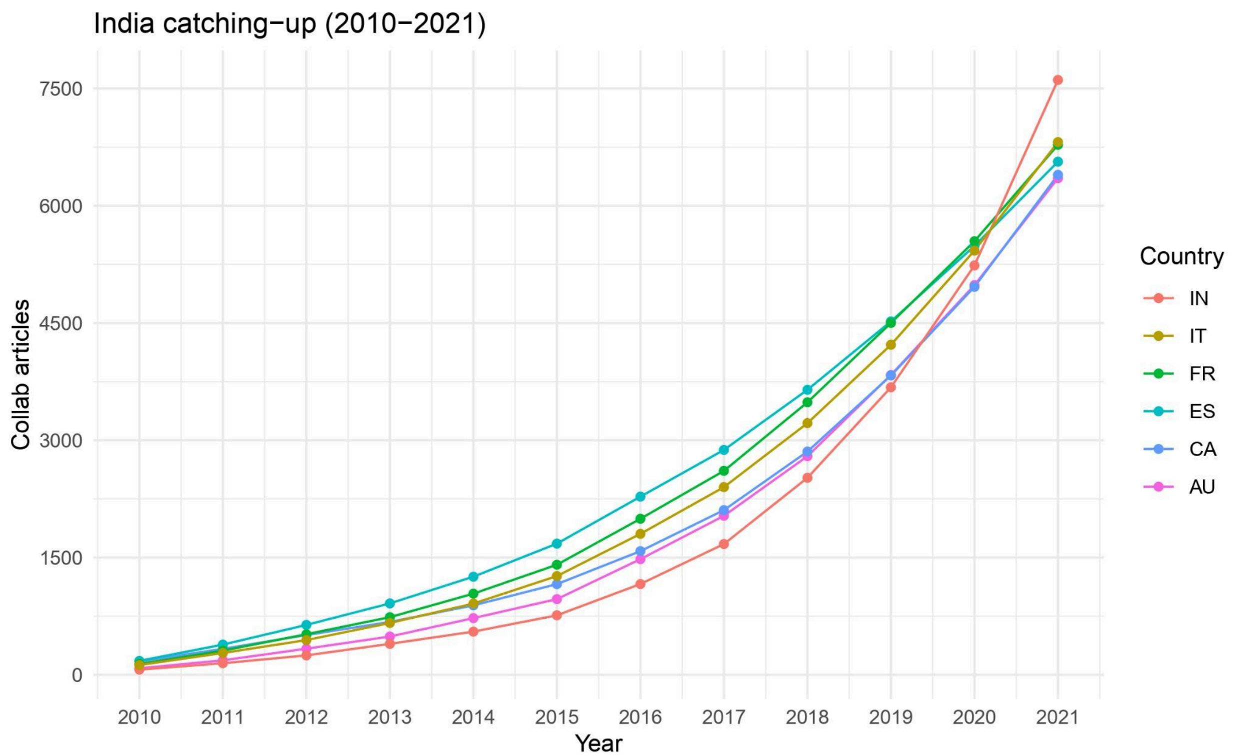


Source: our elaboration based on data from the Web of Science.

The disparity between individual article analysis and interaction analysis can be attributed to two main factors. Firstly, while the articles count a publication towards the country of the first author's university, interactions account for all authors. This could mean that the US has multiple authors collaborating with a primary author from another country. Secondly, interactions involve numerous universities, suggesting that internationally co-authored articles may include several US researchers from various institutions. Regardless, the interaction analysis underscores the significant role the US plays in international collaborative articles, establishing it as a key reference point in AI research.

In the top 10 universities for first-authored AI collaborative articles, most are in China, with two notable exceptions from Singapore, including Nanyang Technological University at the highest rank for the country. The Chinese Academy of Sciences has been at the forefront of this ranking annually since 2011. For 2021, universities from other nations, such as the University of Oxford in Great Britain and Islamic Azad University in Iran, have also secured strong positions, indicating a rising trend in their research output.

Figure 4 - India catching-up



Source: our elaboration based on data from the Web of Science.

Table 2 - Main collaborator by interactions

China-inclined Total: 10 countries (5%)		**US-inclined** Total: 100 countries (53%)		**GB-inclined** Total: 24 countries (13%)	
Country	Interactions	Country	Interactions	Country	Interactions
US	86829	CN	86829	SA	5475
AU	20252	GB	65611	PK	3718
SG	11286	IT	56926	IE	3386
IS	147	DE	47532	PE	2971

KZ	127	CA	38492	NG	1611
RW	65	FR	29642	PH	1408

Source: our elaboration based on data from the Web of Science.

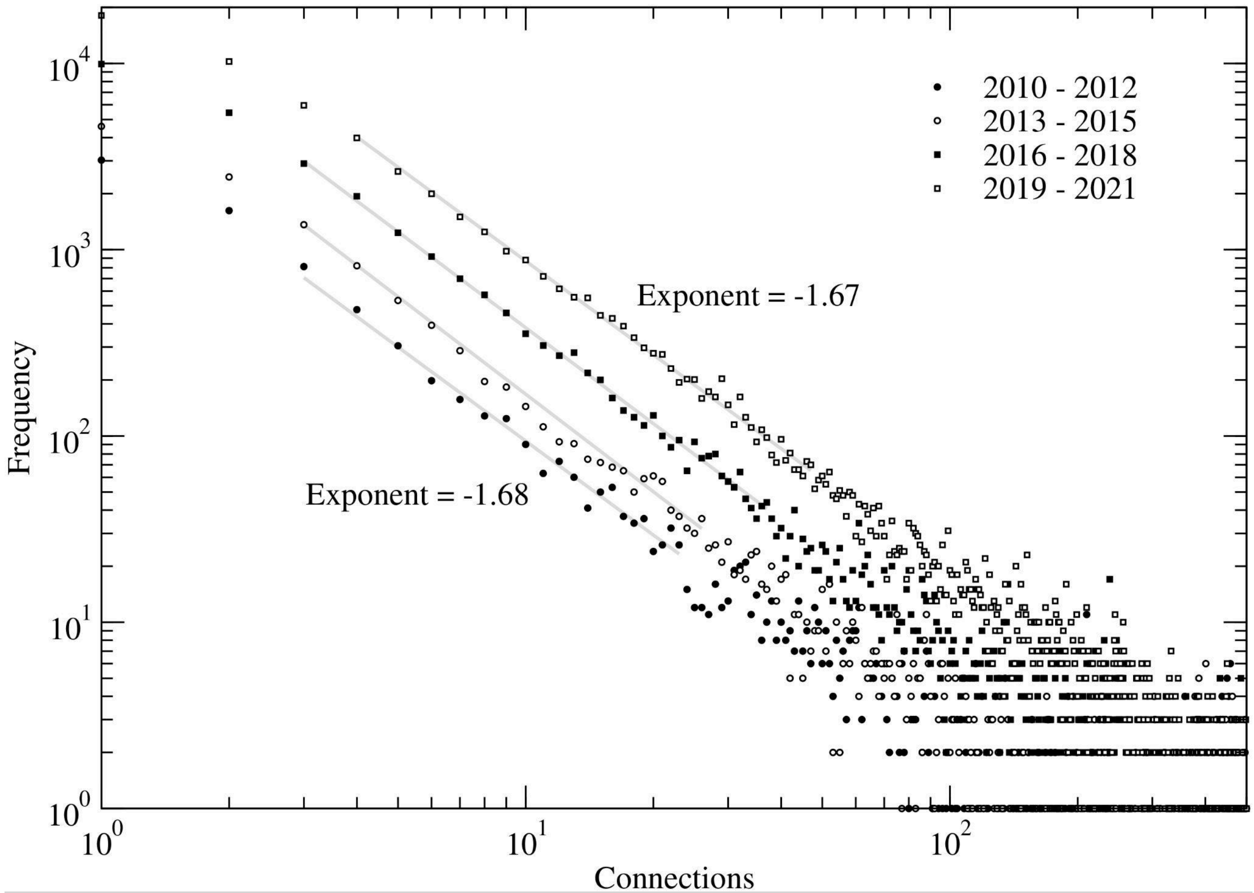
Table 3 - University ranking

Rank	Country	University	Articles
1	CN	Chinese Acad Sci	2295
2	CN	Tsinghua Univ	1810
3	SG	Nanyang Technol Univ	1573
4	CN	Zhejiang Univ	1420
5	CN	Shanghai Jiao Tong Univ	1383
13	GB	Univ Oxford	853
15	CH	Swiss Fed Inst Technol	777
21	IR	Islamic Azad Univ	512
25	MY	Univ Malaya	291
29	US	Stanford Univ	202
37	DE	Tech Univ Munich	122
38	BE	Katholieke Univ Leuven	103
39	AU	Univ Technol Sydney	101

Source: our elaboration based on data from the Web of Science.

Figure 5 illustrates the network shaped by international co-authorship in AI scientific publications. The network's behavior aligns with a power-law curve, indicative of a free-scale network structure (BARABÁSI; ALBERT, 1999) - a hallmark of complex systems. Notably, this network has maintained a consistent structure over time, preserving a similar hierarchy throughout the observed periods.

Figure 5 - Network behavior



Source: our elaboration based on data from the Web of Science.

5 Discussion

Our exploration of complex systems, inspired by the research conducted at the Santa Fé Institute, provides insights into the nature of knowledge flow in the field of AI. Complex systems, characterized by non-linear responses, diverse behaviors across different scales, and the 'more is different' principle, are present in AI research. Examples such as the sandpile and El Farol models illustrate the presence of non-linear and self-referential dynamics within AI research, while these insights into the challenges posed by rational expectations serve as further evidence of the intricate nature of the field.

Our findings highlight the vital importance of knowledge flows in AI. The fact that more than 21% of AI-related articles are internationally co-authored emphasizes the complex network of global connections within the AI research community. This reflects a robust commitment to cross-border knowledge exchange, enhancing global and cross-cultural expertise sharing. Such insights offer crucial guidance for those seeking to fully exploit AI research on an international level.

China’s prominence in the global AI scientific landscape is remarkable, as it competes vigorously with the United States. According to (UNCTAD, 2019), the conventional center-periphery division is being challenged by China's rise as a major global competitor, consistently persistently challenging the US for supremacy in key technologies of the digital economy. Both countries have evolved into pivotal forces in the digital realm (LI; QI, 2022):

> These two economies account for 75 per cent of all patents related to blockchain technologies, 50 per cent of global spending on IoT, at least 75 per cent of the cloud computing market, and for 90 per cent of the market capitalization value of the world’s 70 largest digital platform companies. The United States alone also hosts 40 per cent of the world’s colocation centres (UNCTAD, 2019, p. 21).

On a global scale, China plays a prominent role in all emerging technologies, being among the leading nations to master them. Specifically, in the realms of Artificial Intelligence and data analysis: “China, the United States, and Japan together account for 78 per cent of all AI patent filings in the world” (pp. 8-9). In its Technology and Innovation Report 2021, UNCTAD (2021) underscores China's pivotal involvement in eleven cutting-edge technologies: Artificial Intelligence, Internet of Things (IoT), Big data, Blockchain, 5G, 3D Printing, Robotics, Drones, Gene Editing, Nanotechnology, and Photovoltaic Solar Panels. In all the listed frontier technologies, China consistently ranks among the top contenders, frequently competing for leadership with the United States. Noteworthy contributions come from various Chinese universities and ministries, with standout entities including the Chinese Academy of Sciences and the Ministry of Education of China. Among the key firms involved, the study highlights Alibaba (blockchain), Huawei (5G), ZTE (5G), KUKA (robotics), DJI Innovations (drones), Yuneec (drones), Jinko Solar (photovoltaic panels), JA Solar (photovoltaic panels), and Trina Solar (photovoltaic panels) (p. 21).

The state plays a pivotal role in shaping the direction of innovation and the growth of the digital economy in a country, with the unique alignment between the state and the private sector in China being a potential explanation for the country's success in artificial intelligence (BERAJA; YANG; YUCHTMAN, 2023). In their case study, the authors identify 7,837 artificial intelligence firms specializing in facial recognition in China, many of which establish multiple government contracts. Empirical results indicate that the benefits of these government contracts outweigh resource crowding-out effects, leading firms to achieve economies of scope in artificial intelligence innovation through data sharing for both government and commercial purposes (p. 21). The authors highlight the Chinese government's capacity to adopt a data-driven industrial policy due to its strong state presence: “there will be around 560 million public surveillance cameras installed in China by 2021, versus approximately 85 million in the US” (p. 39). This characteristic can, therefore, be seen as an advantage for innovation in the Digital Age.

Industrial policy has also played a pivotal role in China's mastery of emerging technologies. Since at least 2006, the Chinese government's resolute commitment to an aggressive industrial policy, increasingly focused on mastering technologies not yet fully established in the rest of the world, has been notable (NAUGHTON, 2021). Initiatives such as MLP, Made in China 2025, Internet Plus Program, and Innovation-Driven Development Strategy have been instrumental in expediting the advancement of digital technologies in the country, including AI (SUN; CAO, 2021).

It is important to consider that firms do not exhibit uniform behavior and adopt various strategies within the sector. Rikap (2023) demonstrates that among American big tech companies, Microsoft plays a unique role in bridging China with the West, as “by being both deeply related to several US and European universities and widely established in China, Microsoft unifies the frontier AI field” (p. 9). In the author's study, the Chinese Academy of Science is the organization with the highest frequency of presentations, followed by Google and Microsoft. However, the former ranks twelfth in betweenness centrality, suggesting, by this metric, that China maintains a “relative detachment from the rest of the world” (p. 9). This characteristic was not identified through our methodology and suggests a potential avenue for the advancement of our research.

Despite the significant presence of the Global South among the top ten countries in AI article production, as evidenced by China, India, and Iran, Latin American countries largely find themselves outside the prominent positions. Brazil stands as an exception, ranking 16th in terms of AI articles with 17,069 publications, 3,393 of which are the result of international collaboration (20%). New strategies must be adopted to promote innovation in the region. As emphasized by Lundvall & Rikap (2022), regional integration strategies can be an important measure to confront the power of tech giants. However, it remains largely uncertain whether Latin American and African countries can catch up with global leaders. The recent example of China's catching up (LEE, 2021) serves as a significant case, providing valuable insights for science and technology policies in the Global South.

6 Final comments

The emergence of the Digital Era, characterized by the exponential growth of digital data, has ushered in a new wave of transformations, with artificial intelligence (AI) at its forefront. AI's disruptive potential in the economy and innovation processes cannot be overstated, possibly marking it as a General Purpose Technology with the capacity to reshape global innovation. Nevertheless, these advancements are not uniform across nations, creating a global divide in digital capabilities that poses significant challenges for Global South countries.

In our investigation, we identified a total of 1,097,821 AI academic articles worldwide from 2010 to 2021, from which 235,932 (21%) featured international collaborations, signifying a significant international knowledge flow within the AI sector. China emerged as the dominant contributor, with the most AI articles both overall and in international co-authorship, followed by the United States. Three BRICS+ countries, including China, India, and Iran, featured prominently among the top AI contributors. Among universities, the Chinese Academy of Sciences and Tsinghua University led in AI articles with international flows.

The network of international co-authorship in AI publications follows a power-law distribution, indicating a free-scale network structure. This observation highlights the relevance of complex systems in our understanding of academic collaboration. By embracing the principles of complex systems, we gain valuable insights into the intricate dynamics of global scientific partnerships within AI research. Following the “more is different” principle, our study suggests that in international collaborations, the cumulative effect of diverse contributors can lead to emergent and transformative outcomes.

Our analysis has shed light on the possible emergence of global innovation systems, influenced by the increasing global connectivity among actors and institutions engaged in innovation activities. This global layer complements existing national, regional, and sectoral dimensions, facilitating knowledge exchange between countries and potentially reshaping the hierarchy and complexity of the overall innovation system.

China plays a central role in emerging technologies and AI research. China's aggressive industrial policy, such as Made in China 2025 and the Innovation-Driven Development Strategy, has furthered its leadership. While several Global South countries contribute to AI research, Latin American countries need new strategies to compete with tech giants. Brazil stands out, ranking 16th globally in AI article production. We believe the Chinese catching-up provides insights for science and technology policy in the Global South.

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