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Artificial Intelligence and International System Structure

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Abstract

Previous studies have investigated technology's impact on international affairs, but few have analyzed the effect of artificial intelligence on the international system structure. This study integrates heterogeneous datasets and network science concepts with several power factors and artificial intelligence advances as a methodology to understand the evolution of the international system with a perspective around research, knowledge, innovation, and technology as an endogenous variable. Our findings indicate that the international fitness variable could be considered as a mechanism to interpret the system dynamics, especially when artificial intelligence interacts with different topics of the system. Overall, we provide quantitative evidence of the evolution of artificial intelligence innovations and technological power to identify system structure changes, both in central and peripheral countries.

Keywords: Artificial Intelligence; Center-Periphery; International Fitness; International Power; Network Science

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Introduction

Artificial Intelligence (AI) increasingly mediates the way we interact with others. However, the implications in the structure of the international system and international power distribution have not been addressed by international relations literature. Power dimensions define the international position of states affected by AI and display a complex system that involves economic, military, diplomatic, financial, and technological dimensions. Therefore, we ask: what kind of world structure emerges from interactions with technology concentrated in some cases, but distributed in others? How do technology and innovation transform international power factors? Which international power factors will remain relevant? What about peripheral countries?

Previous research has defined that interactions between research, knowledge, innovation, and technology created a new

perspective on productivity and competitiveness. The concept of central regions in center-periphery models (Ferrão and Jensen-Butler 1984) could be changed, because international fitness is an element to define new interactions in the dynamics of the international system. In other words, peripheral countries could interact with other countries from central regions beyond traditional factors, such as labor, commodities, and capital, because they built a new international fitness that resulted of research, knowledge, and innovation. With AI, international power traditionally constituted by economic, military, diplomatic, and political capabilities, will bring new benefits to any country with the technical capabilities and knowledge to use them.

Science and technology has been a neglected issue in the international relations research agenda (Fritsch 2011; Weiss 2015). A branch of literature about IR and AI emerged in recent years with some limitations. Some use a theoretical and scenario-planning approach (Horowitz 2018; Johnson 2019) or recognize the lack of empirical data (Horowitz 2020). Other studies analyzed specific countries and their challenges (Wright 2019), military affairs, strategic studies, war, and cyberspace (Johnson 2019; Sechser et al. 2019; Horowitz 2020). However, these studies focused on specific power dimensions and did not use the total concept. In this paper, we address this gap by investigating the transformations of the international system structure using empirical research.

For this, we developed a model that includes a fitness model (the ability to compete for links) and a multilayer network. We reviewed previous international affairs studies that used network science. These methodologies allow us to analyze historical changes in the international system (Maoz 2010) or its specific components, such as global finance (Winecoff 2015), trade and conflict (Dorussen et al. 2016), international institutions (Böhmelt and Spilker 2016), international bargaining (Nebus and Rufin 2010), diplomacy (Kinne 2014), international terrorism (Zech and Gabbay 2016), and foreign policy analysis (Slaughter 2017). Thus, network science is useful in international affairs studies, because it helps us understand power distribution and relationship patterns (Hafner-Burton et al. 2009). Consequently, we assembled a multilayer network across four heterogeneous layers observed at three different moments after 2000. We included two analyses: first, traditional international power dimensions as a single layer, and second, those same two with artificial intelligence factors.

Our paper aims for new perspectives on the relationship between fitness and country centrality in the international power network and its dynamics, by analyzing specific factors to understand the system structure and the power network complexity. Those factors, like exports, foreign direct investment, diplomatic posts, and arms trade as a proxy of trade, financial, diplomatic, and military power, respectively, as well as technological patents, publications, experts, startups, and companies as a proxy of artificial intelligence, are one of several possibilities to identify the complex and non-linear power interactions. This paper is an exploration, and our contribution is to show how new knowledge-based material capacities, like Artificial Intelligence, interact in the international system, as well as its implications. This complex system has an intricate structure and a temporal evolution that needs collective analysis. Additionally, we try to demonstrate the deepening of the international system's center-periphery structure, where central countries have

power in different dimensions because of the evolution of technological power and its international fitness to develop it.

We organized this paper as follows. Section 2 describes some preliminary and conceptual approaches to technology and international power. Section 3 presents the data collection and data analysis. Section 4 presents the details the applied research method. Section 5 illustrates our results and discusses the study's findings. Finally, the last section discusses our contribution to the literature, the overall theoretical and practical impact of this study, along with its limitations and suggestions for future research.

Technology and International Power

Building upon previous studies that analyzed the relationship between international affairs and technology, we identified some concepts to develop a multilayer structure. We defined international power as a complex system instead of analyzing each of its parts in isolation, and we focused on artificial intelligence as a dimension that interacts with traditional powers. Thus, we first explained the complexity of international power. Second, we shortly analyzed the role of agency and identity in technological development. Third, we described the endogenous nature of interactions between power and technology. Fourth, we presented the complexity of the artificial intelligence ecosystem.

The complexity of international power

We will begin by defining the complex nature of international power. Given that central authority does not exist above the states, they must resort to self-organization to survive. So, the concept of power is key to analyze international system structure (Barnett and Duvall 2005) and can be understood in the following way: "A has power over B to the extent that he can get B to do something that B would not otherwise do" (Dahl 1957, 202-203). Thus, states compete to achieve power and survive (Waltz 1993; Mearsheimer 2001). Given that power could be exerted through different means (e.g., coercion and deterrence) and several dimensions (e.g., military, economic, and diplomatic), their dynamic interaction means that international power is a complex system (Barnett and Duvall 2005; Root 2017).

Hard power is achieved by the combination of economic, financial, and military capabilities (Mearsheimer 2001; Waltz 2010). Soft power is the influence of diplomatic and cultural ties (Nye 1990), which confers network centrality, and therefore power in a world interconnected by information technologies (Slaughter 2017). Military power in particular requires economic, financial, scientific, and technological capabilities, because weapons development and wars are not free (Posen 2003; Beckley 2010; Gilli and Gilli 2019; Mearsheimer 2001). Also, financial power can be used as a coercion tool and an instrument for attraction, as it is in the middle of the categorization (Blackwill and Harris 2016). Finally, diplomatic ties enable countries to achieve economic, scientific, and military alliances that influence international position (Henke 2017;

Eichengreen et al. 2019), while economic and military capabilities facilitate diplomatic network development (Helleiner 2013). In consequence, power dimensions are deeply interdependent, constituting a complex system.

Agency and identity in technological development

Given that states struggle to survive, they need to achieve power. But the old formula of developing economic power and then transforming it into military capabilities is already useless, because complex modern science and technology are necessary conditions to achieve economic and military advance (Brooks and Wohlforth 2016). Moreover, the scientific know-how required to create power is harder to copy from other states, given its increasing complexity through time (Gilli and Gilli 2019). Hence, the pressure of international competition and the complexity of scientific progress force states to expand their scientific ecosystem (Taylor 2016).

That implicit agency in the innovation process is one of the main reasons for structural change in the international system. While it is an individual state-level decision, the aggregate generates emergent properties given by system complexity, where science is a part of the power dimension. System changes influence the decisions of actors, who identify a stronger competition and increase their internal efforts (Taylor 2016). Thus, the complexity of the international system allows us to understand the relationship between agency and structure. However, for some scholars, the actors' identity is relevant to the debate both on the international power and technology, and on agency and structure.

Understood as shared constructed ideas (Wendt 1999), identity influences and is influenced by technology (McCarthy 2015), which means that not all actors develop and use power and technology the same way. Returning to Wendt's classic example, that the US does not perceive five bombs possessed by Iran the same as 500 by the UK, one could imagine a similar analysis on AI's capabilities. In this paper, we focus on the concept of structural power as material power, as defined by Barnett and Duvall (2005), because it allows us to set an initial big picture to continue our research agenda.

The endogenous nature of interaction between power and technology

After describing the complex nature of international power and its development, we will describe the relationship between international power and technology. First, technology is defined as "any application of organized technical knowledge [...] for a practical purpose or the capacity to develop and use such knowledge" (Weiss 2015, 412). Traditional approaches consider technology as an exogenous variable with distributional properties (Drezner 2019). Given that technological change reorders military and economic capabilities, modifies international economic relations, creates new resources, and establishes relations among actors (Weiss 2015), technology is a tool to achieve foreign policy objectives and compete internationally (Smith 2020). Hence, technological

development contributes to change the balance of power among nations (Gilpin 1981). In the quest for power, several states copy or develop new technologies, thus reducing, or eliminating, previous advantages achieved by others.

However, there is a lack of conceptualization of technology in the discipline. Understanding technology as a system embedded in social norms and interacting in multi-directional ways (e.g., international politics, values, or competition), led to some scholars treating technology as an endogenous variable, with domestic and intrinsic characteristics (Weiss 2015; Fritsch 2011; Drezner 2019; McCarthy 2015). This approach makes it possible to understand the complex nature and divergence process of technologies. Technology does not represent an external shock to the international system. Besides, it emerges within the system, interacting with and being influenced by other variables.

The complexity of the artificial intelligence ecosystem

This paper is focused on AI as a specific technology. What is it? In this article, we rely on the narrow definition of AI based on machine learning and defined as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings” (Kaplan and Haenlein 2019, 17). Unlike nuclear technology, which was an elite technology with specific purposes, AI is a General-Purpose Technology (GPT) that can be understood as a dimension of power that goes beyond military capabilities, as business, government, healthcare, education, and diplomacy interact with it (Kaplan and Haenlein 2020), which redistributes international power in several dimensions.

Nonetheless, AI is an ecosystem of knowledge of interrelated technologies, which makes it hard to develop, copy, and diffuse. For instance, the main AI applications regard interactions between users and computer developments, a multidisciplinary field known as Human-Computer Interaction (HCI). It involves computer science, cognitive science and engineering to create a way to integrate technology in everyday life as well as designing it for human users (MacKenzie 2013). AI requires a complex ecosystem based on data, computational power, and algorithm design (Lee 2018; Buchanan 2020). Furthermore, HCI creates a cycle in which better interfaces and usage lead to more data and users, resulting in better AI algorithms and new possibilities to enhance HCI. Therefore, AI development and its benefits will not be widely distributed. These theoretical assumptions imply that, first, few states can develop AI capabilities; second, AI interacts with another dimension of power; third, AI is deepening the existent center-periphery structure driven by a technological gap.

Data Collection and Analysis

We separated the data in three groups. The first group consists of annual figures of four variables that represented the interaction between countries, more specifically, exports FOB (for some countries we used 2017 data), foreign direct investment (outflows), military exports, and

diplomatic interactions. We obtained these data from the World Bank (World Bank 2019a), the International Monetary Fund (IMF 2019a), the Stockholm International Peace Research Institute (SIPRI 2019a), the Global Diplomacy Index (Lowy Institute 2019), and the Correlates of War Diplomatic Exchange (Bayer 2006), respectively. We have obtained most information from countries' foreign ministries to check the diplomatic posts and constructed a diplomacy dataset for all countries to complement the diplomatic dataset. After manual processing, we have obtained a data set that contains the diplomatic posts of 213 countries with 10,214 interactions.

The second group consists of four variables that represented the international power of countries in four aspects: GDP as an economic power, international reserves as financial power, the scale of UN assessments as a diplomatic power, and military expenditure as a military power. The sources were the World Bank (World Bank 2019b), the International Monetary Fund (IMF 2019a), the United Nations (2018), and the Stockholm International Peace Research Institute (SIPRI 2019b), respectively.

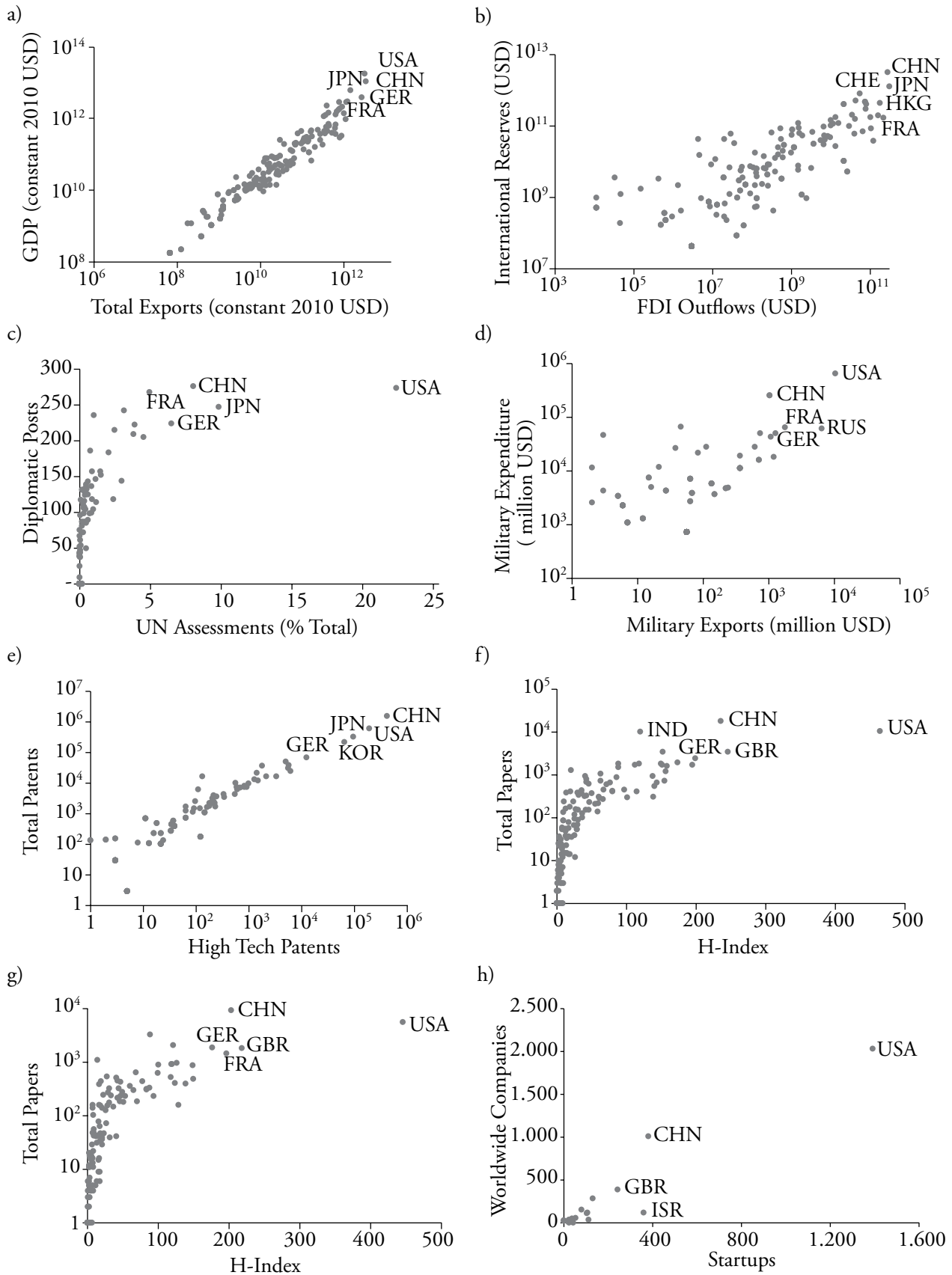
The third group consists of two subgroups. On the one hand, patents evolution, artificial intelligence and human-computer interaction publications by country. Those metrics approximate human capital and innovation and are the standard metrics used by several global AI reports (Capgemini Consulting 2018; McKinsey Global Institute 2018; Baruffaldi et al. 2020; Tortoise 2020; Nature 2020; Zhang et al. 2021) and by researchers studying innovation development and its future (Acemoglu et al. 2016; Pugliese et al. 2019).

Although publications are an incomplete measure, given the non-published results carried out by some public agencies and private companies, they have been a proxy and reliable measure of AI capabilities (McKinsey Global Institute 2018). On the other hand, artificial intelligence variables, such as companies, experts, and startups as a proxy of AI power, were compiled from the World Intellectual Property Organization, the Scimago Journal and the Country Rank for the first subgroup. The AI Development Report was elaborated by the China Institute for Science and Technology Policy at Tsinghua University, and the AI Report by Roland Berger for the second group.

A single data analysis allowed us to understand the evolution of four variables of international power, as well as the technology power evolution. The first coefficient is the relation between GDP and exports as an economic power proxy (Figure 1a). The second is the relation between international reserves and foreign direct investment outflows as a financial power proxy (Figure 1b). The third is the relation between diplomatic posts around the world and UN assessments as a proxy of diplomatic power (Figure 1c). The fourth is a result of the relation between military expenditure and military exports as a proxy of military power (Figure 1d).

In the case of technological power, we develop several coefficients. The first is the relation between total patents and high technology patents (Figure 1e), the second is the relation between total artificial intelligence papers with their H-index (Figure 1f), the third is similar, with pattern recognition papers (Figure 1g), and finally, the relation between worldwide artificial intelligence companies versus startups (Figure 1h).

Figure 1. Some Patterns of International Power 2018



a. Economic Power (GDP vs. Exports). b. Financial Power (International Reserves vs. FDI). c. Diplomatic Power (UN Assessments vs. Diplomatic Posts). d. Military Power (Military expenditure vs. Military exports). e. Technological Power (Patents vs. High Technology Patent Publication). f. Artificial Intelligence Power 1 (Artificial Intelligence Papers). g. Artificial Intelligence Power 2 (Pattern recognition Papers). h. Artificial Intelligence Power 3 (Worldwide Companies vs. Startups).

Methods

International Fitness

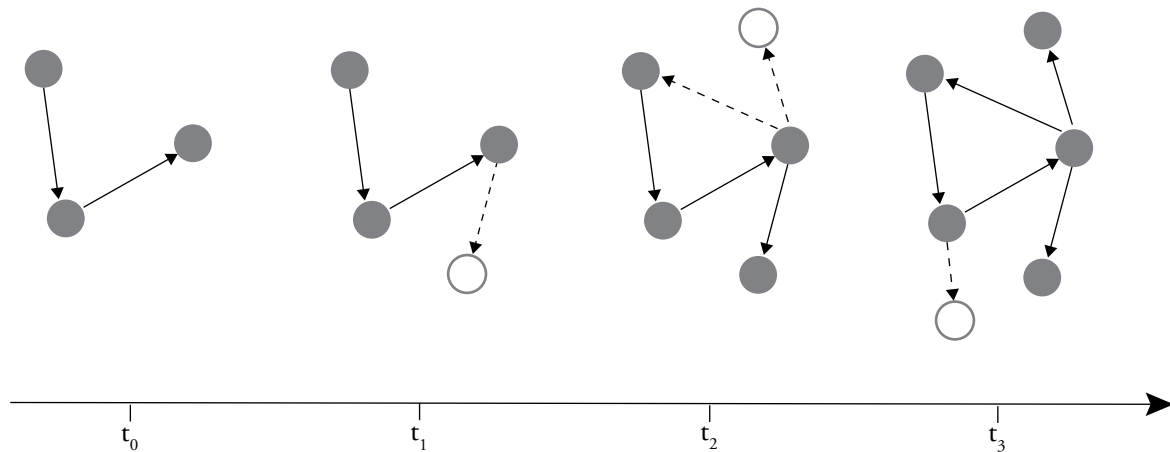
Complex systems that involve individuals' actions and decisions, as countries do, may give rise to collective phenomena that cannot be explained using individual analysis, i.e., the temporal evolution of complex systems cannot be explained as a behavior function of its isolated components (Bar-Yam 1997). Therefore, countries have different endogenous abilities to compete for influence and power in the international system, and they could develop those abilities if they are interested in developing them, have capacities to do so, and compete for links with other countries. To identify those differences, we used network science tools. In order to identify them, we assigned each country with a fitness parameter η_i chosen from the distribution $\rho(\eta)$ and the maximum possible fitness in the world system determined by η_{max} (see details in Mathematical Appendix). The complexity of the world system establishes a finite number of countries with different levels of interactions. However, we supposed a world system with a small group of countries in t_0 and we added a new country ti and interaction in t_1 , and so on, until t_n , as a seed network (Figure 2).

Each new country connects to countries in the world system, and the probability P_i of this connection depends on connectivity k_p , influenced by preferential attachment π and fitness η_i (Pham et al. 2016). Thus: $P_i = \frac{\eta_i \pi(k_i)}{\sum_j \eta_j \pi(k_j)}$. Namely, if the country does not have these elements, it is likely that it is part of the periphery, because not all countries are successful in international influence competitions, they appear at different times and grow at different rates. However, the highly connected countries could dominate connectivity. To simplify, we assume that $\pi(k) = k$, thus, a country will increase its connectivity k_p , at a rate that is proportional to the probability P_i that a new country will attach to it, so each new country of the world system adds μ links to the system (Bianconi and Barabási 2001). Additionally, the evolution of connectivity $k_i(t)$ established that all countries increase their connectivity in time. First intuitions might lead to the idea that the oldest countries would have the highest number of interactions, since they have been present for longer in the world system, but the probability $P(k)$ that a country in the world system interacts with other countries reduces as a power law (Barabási and Albert 1999).

Countries habitually define their connections based on their preferential attachment and other opportunities with their fitness, which means that the time dependence of a country's connectivity is based on its fitness η_i . In this case, the connectivity distribution notated by probability $P(k)$ is a result of a weighted sum over different power laws.

Multilayer network of international power

With the international fitness model, we created a multilayer network of international power with the following elements. First, we defined a single layer network $G(V,E)$ as a set of countries V , coupled with a set of edges E describing the relations between them in a specific issue. Second, a

Figure 2. Growing Network

At each $t+n$, new countries and links are added to the world system. The grey node represents an old country and the white node a new one(i).

multilayer network was formed by V countries $i = 1, 2, \dots, V$ and L layers $\alpha = L_1, L_2, \dots, L$; i.e., the multilayer network, $M = (V_M, E_M, V, L)$ i.e., each layer is a specific network of the world system described by an adjacency matrix A^α (Kivela et al. 2014; Iacovacci and Bianconi 2016). Third, we defined a multilayer network where the link does not connect the layers, but the layers share the same set of countries (Bonaccorsi et al. 2019). Fourth, we established directed and weighted layers, and elements of the adjacency matrix take the value $A_{ij}^\alpha = w_{ij}^\alpha$ if the directed link for country j to country i has weight w_{ij}^α , and $A_{ij}^\alpha = 0$. Thus, we established a difference between the in-degree $k_i^{in,\alpha}$ and the out-degree $k_i^{out,\alpha}$ of country i in layer α . This way, the assembling of a sequence of elementary layers allows for a multilayered network from the elementary layer combinations (Kivela et al. 2014). The types of participation and interactions of a country i at time t are given by a matrix formed by a set of elementary layers that represent factors of international power (Figure 3a). Thus, the world system was encoded by matrices $A^\alpha(t)$ and represented by layers $\alpha = L_1, L_2, \dots, L_\alpha$ with different weighted combinations $w_\alpha(t)$ (Figure 3b). The model could obtain several correlations between layers and the emergence of the multiplex network structure that represented the evolution of structure of the international system and the identification of countries that have a significant role in the international system (Figure 3c). Namely, preferential attachment and fitness define the system interactions, and the hypothesis of random distribution of links among the countries is not significant.

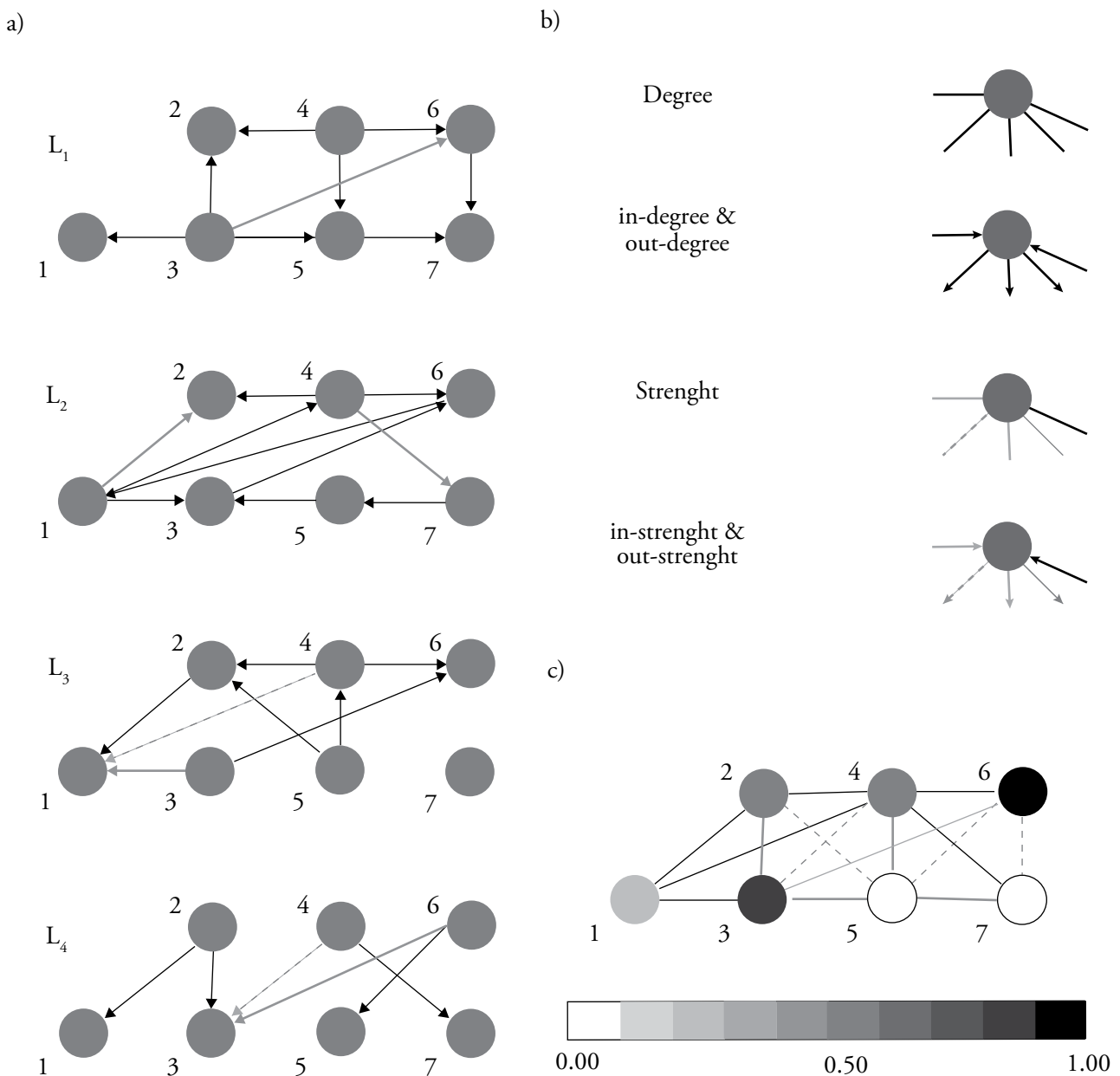
In the international system, countries are not equivalent. Some network science methods in weighted networks identify the influential nodes as the degree centrality, the betweenness centrality, and closeness centrality (Barrat et al. 2004; Newman 2004; Opsahl et al. 2010). However, node connectivity in these networks depends on not only its neighbors' number but the connection strengths between them, as well as the distribution of the total strengths on each edge (Hu and Mei 2018). For this reason, we propose a ranking that considers the country connectivity strengths, connecting edges, distributions of the total connectivity strengths on its connecting edges, and additionally, equivalence to the value of variables that are not interactions, such as GDP, international reserves, UN assessments, and military expenditure. Besides, this model explores a new approach to the power of each country, especially the inclusion of material capacities that are not always quantifiable.

Results

International Fitness, Power, and International System Structure

In this section, we use the international fitness and multilayer network methods discussed in Section 3, as well as the data analysis of the same section. Figure 4 reports the results of the international fitness model combination with the different layers of international power and weighted nodes for the 2018 snapshot. We determined whether network structure and center-periphery structures define the artificial intelligence international system structure. For robustness, we used different layer weights, but the results did not change significantly with these weights.

Figure 3. Multilayer Network



a) Layers $\alpha = L_1, L_2, L_3, L_4$ of the world system. b) Nodes and the expected force. c) The weighted combinations allow us to build the overall layer.

We can see that this choice of international power parameters confirms the center-periphery scheme. In the first layer (economic power), we find a structure that fulfills the model expectations on which countries are more relevant in international trade, especially exports of goods and services. The structure for the four snapshots is similar, except for the ascent of China and its centrality period by period (2000 to 2018). Additionally, we show that China and the United States each create a hub (Figure 4a), but some central countries orbit between them, such as Japan, Canada, and the United Kingdom.

These results show that some countries developed their interactions because of international fitness and not as an exclusive result of preferential attachment. In the financial power layer, some countries with specific international fitness as advanced financial markets (Luxembourg, Switzerland, and Netherlands) showed up at the center of Figure 4b. However, the connectivity between those countries and the China-United States axis creates a measure of financial flows and foreign direct investments, which use some financial centers to develop them. In this case, some tax haven countries could affect the structure, but these countries are not relevant to the layer.

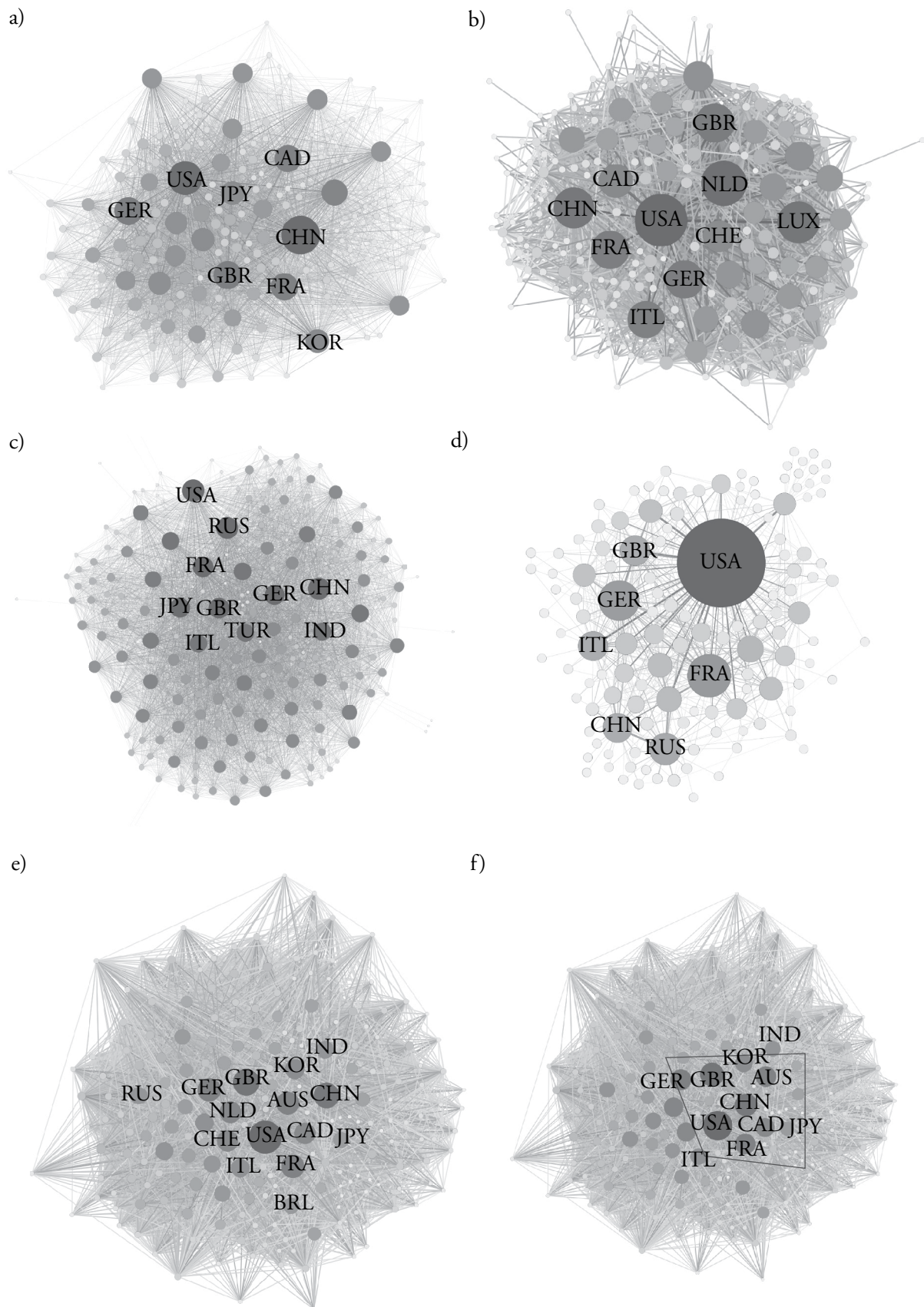
Additionally, European countries such as Germany, France, and Italy show their financial fitness through foreign direct investment flows as well as their strength to develop the connectivity k_j .

The layer of diplomatic power shows diplomatic mission posts because of countries' national interests. Some countries could prefer to connect only with their neighbors (preferential attachment) as it happens in some cases, but some countries in the periphery connect with central countries that have a better position in diplomatic order, countries with international fitness to attract them (Figure 4c). The military layer shows the participation of many countries, but in the contracts it is possible to identify that some concentrate high military technology exports. The result is the attraction of countries interested in this technology to strengthen military power. The single layer shows that some countries have a better central position than others in the multilayer network α (Figure 4e). International fitness presents better performance because we integrated the international power capacities.

Now we integrate the technology and artificial intelligence rankings. Our final goal is to include the weighted nodes and how technology proxies could change the multilayer structure. First, we find that the technological and artificial intelligence variables, proxies of new international power, are statistically significant and positive in the weighted nodes. We also verify that the in- and out-strength positively relates to artificial intelligence evolution. Although the centrality indicators confirm international fitness, the weighted nodes show a small topological change because some countries reduce their centrality indicators while others improve them (Figure 4f).

However, we confirm that countries with great international fitness are the ones who develop most knowledge, research, innovation, and technology processes. Thereby, countries that create an artificial intelligence ecosystem from the integration with other international power factors achieve centrality of international system, which means that countries could stay in the center if they maintained and consolidated other international power factors.

Figure 4. International Fitness and Power Interactions



a) Economic Power Layer, N=208; E= 5,661. b) Financial Power Layer, N= 207; E= 4,580. c) Diplomatic Power Layer, N=213; E=10,214. d) Military Power Layer, N=130; E=580. e) Multilayer Network of International Power. N=213; E=11,509. f) International Power Multilayer Network +Technological and AI Powers (Dark grey line).

As a layer of international power, technology power feeds on other international power layers. In other words, the international system structure depends on international fitness. Artificial intelligence is a part of a complex system structure and is not an isolated technological process led by a group of companies. Therefore, countries could advance into the artificial intelligence ecosystem if they develop their international fitness. We obtained interesting results with the implementation of specific weight (w_i) to technological and artificial intelligence proxies for countries with a high international fitness performance. Some countries, like Switzerland and the Netherlands, reduced their international fitness, but peripheral countries consolidated their position.

AI functioning requirements are conferring superiority to the countries that have a more developed ecosystem, thus redistributing power and deepening the current center-periphery structure of the international system. Two countries are currently at the lead, US and China, followed by a group of countries with increasing interests in the sector but in which it is necessary to strengthen their international fitness to catch them.

In sum, we find that artificial intelligence and international power are closely related to central countries because the evolution of technological and artificial intelligence powers needs the other international powers' evolution. Besides, this process is not autonomous because any advance of artificial intelligence will frame in the advancement of other technological, financial, and research affairs in which international fitness is fundamental.

AI and the Periphery

The result trends above present a difficult situation for the periphery because the gap between developing and developed countries could be greater. After all, international power is a result of different factors that include technological capacity. For the next few years, the knowledge to develop new human-computer interaction systems and artificial intelligence tools could make all the difference for international power, not just as an instrument of military capacity, but equally so as an instrument of political and economic capacity. In consequence, several countries that do not have a dynamic process of science, technology, and knowledge development could fall to a deeper peripheral position.

The hypothesis of this section is the relevance of a country in the international system through its position in artificial intelligence and human-computer interaction (HCI) publications as a proxy of AI power. In this case, we complemented the AI papers with HCI papers as a coefficient between two variables with special attention in HCI. This topic specializes in technology capabilities, while artificial intelligence is a wider topic that includes a combination of data science, statistics, computer science, among others. As displayed in Figure 5, the effect of the human-computer interaction variable on the coefficient is pronounced even if we did not use the algorithmic scale in this axis. However, we identified that some countries with good performance in artificial intelligence do not necessarily have good performance in HCI, but we also observed that the HCI effect identifies the United States and China as absolute leaders by

2018. Additionally, in the last twenty years, China evolved in this topic, beating technological leaders like Japan, Germany, and the UK.

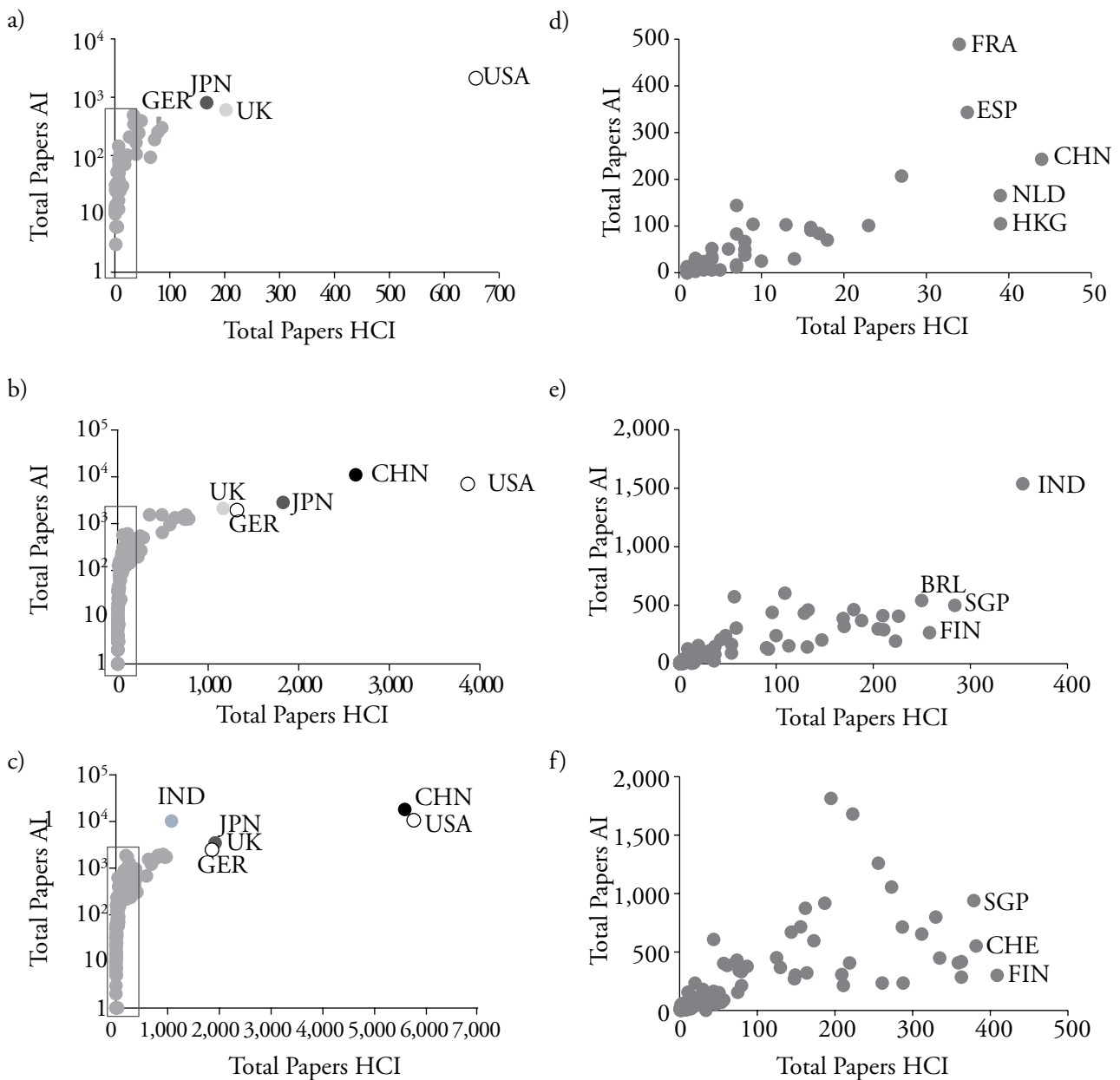
To explain the peripheral countries and the following countries, we add an analysis of the y-axis of the general graphic. These estimates, shown in the right column of Figure 5, identified some countries like Singapore, Finland, Switzerland, Netherlands, and Hong Kong, who built strategies to reduce their gap with the first following group (Japan, Germany, the UK) and the leaders. However, Figure 6 displays marginal effects in other countries in the periphery, except for the case of India and Brazil.

The results support the hypothesis, which stipulates that the difference between leaders and non-leaders will increase over time unless some countries invest and define a specific strategy in science, technology, education, and knowledge. Another perspective suggests that there may be a big difference in terms of knowledge to develop new technology alternatives and AI and HCI methodologies. If an advantage in research leads to superiority in the number of papers and patents, a country could create better infrastructure to develop innovations, hence, several countries have tried to implement this kind of strategy. Therefore, knowledge networks are essential to create a framework to be a country with AI independence, although there may be some countries in the periphery that do not have this capacity. They will be a follower group that needs other countries to implement from simple to complex AI processes. Over time, AI may suggest an increase in the difference between center and periphery countries. To confirm this, we built the evolution of knowledge networks in Artificial Intelligence with a panel for the years 2000, 2010, and 2019, for papers presented in the Association for the Advancement of Artificial Intelligence Conference by affiliation origin of each author.

By 2000, the United States led the AI research ecosystem. 66% of papers came from US institutions, while other countries' affiliation authors created some links with the United States affiliation authors, but the common factor is the interaction among authors from institutions of the same country of origin, including the United States. Some network features are the centrality of the United States, a small cluster around it, and another group of countries at the periphery without any interaction with others, but only between them (Figure 6). For 2010, the AI network presented more countries, but with a particularity of new central nodes with minor relevance and the centrality of the United States. Germany, UK, Australia, Canada, Israel, and China increased their participation as well as their interaction with authors with affiliation to institutions of other countries.

Finally, in 2019, the network showed a new structural characteristic where China and the United States created two hubs of research activity through interactions with institutions in different countries. However, the most important weighted link is China-United States (Figure 6) as well as their self-loop. Behind them, a group of countries with a traditionally robust scheme of research, science, and knowledge, like the UK, France, Germany, Japan, Canada, but with a close group of countries like Israel, Singapore, Hong Kong, Australia, India to list a few with new capacity to develop knowledge in AI. Another pattern was that a growing group of authors with Chinese origins in institutions of countries like the United States, Canada, Australia, the United Kingdom, among others, which means China consolidated its position in the center.

Figure 5. Periphery in the AI International System Structure

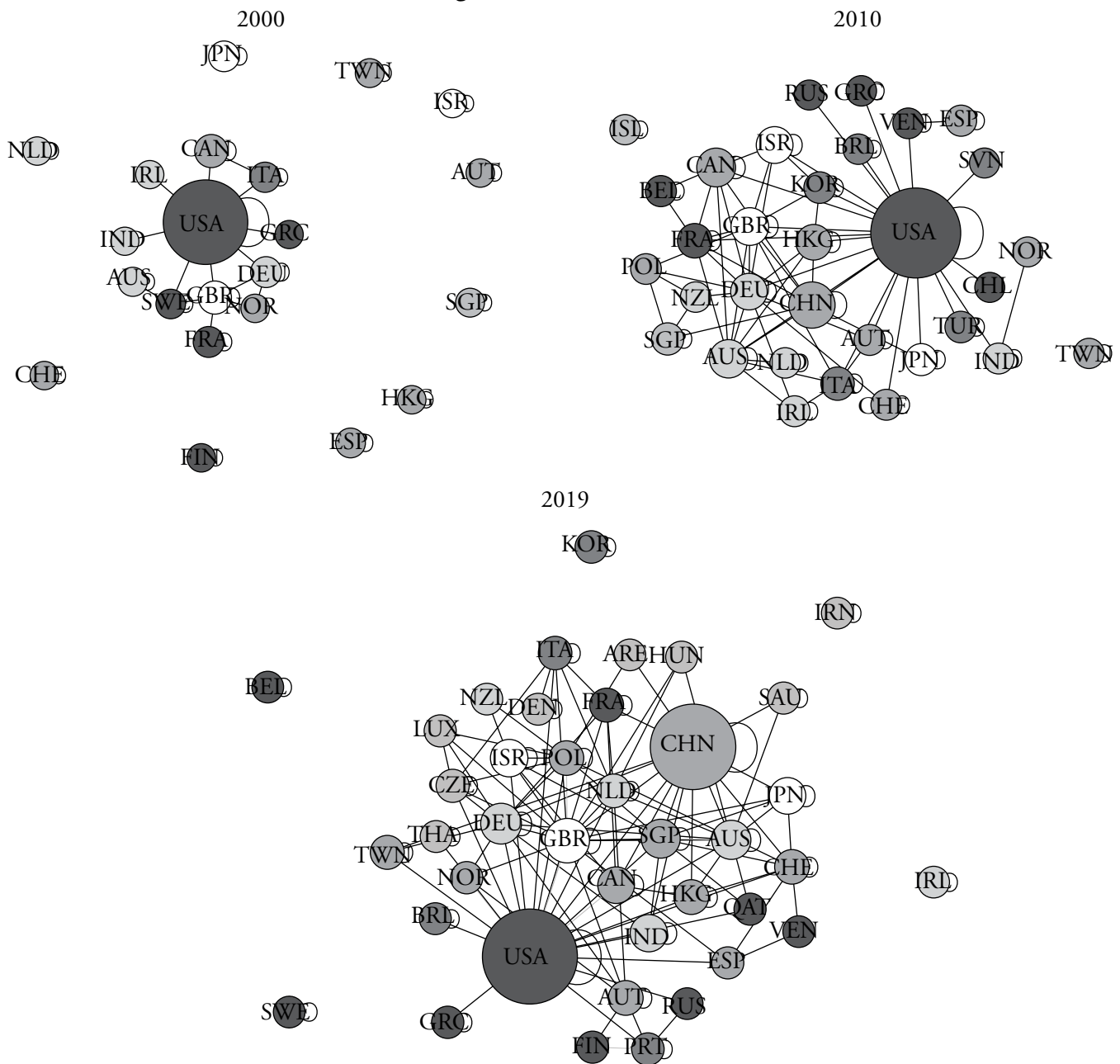


In the three snapshots, most of the peripheral countries did not interact, with some exceptions where interactions are specific or individual. India and Brazil are the peripheral countries with better performance after China. Hence, other peripheral countries move further away from the center and deepen their structural situation in the periphery.

Discussion and Conclusion

This paper revealed the complexity of the current international system. We proposed using network science methodologies to identify the emergence of AI in the international system and the complex interaction between AI and traditional power dimensions. AI implications have been discussed in business, society, and government, but in the context of international power they are

Figure 6. AI Networks



Interactions among authors of the Association for the Advancement of Artificial Intelligence Conference by affiliation origin.

often neglected. Our findings reveal that AI complex interactions with traditional power dimensions could influence the structure of the international system, especially deepening a center-periphery structure led by a few countries with growing power. Based on that, we find three implications. First, AI is a complex system and dynamic source of international power. Second, the data increases its global relevance as a raw material for AI. Third, the international fitness of each country is essential for the evolution of the international system structure when considering AI.

The relation between technology and globalization illustrates these implications. On the one hand, considering that the global knowledge network is a multidirectional system where scientists can move worldwide, it is understandable that countries would try to attract and retain international talent. However, it is also understandable that countries do not share the

knowledge used to develop frontier technologies with some export restrictions, strengthening IP laws, and creating a hostile environment for foreign scientists or companies. As a result, anti-globalization backlash increases the cost of technological knowledge flows by imposing barriers (Buckley and Hashai 2020), such as suspension of highly-skilled workers' visas given to scientists that tech companies usually employ. On the other hand, technological advances also partially explain backlash against globalization as well, given that its consequences in the labor market disruption, profits concentration, and rising inequality (Acemoglu and Restrepo 2020; Autor et al. 2020) are closely related to the rise of populism, one of the sources of anti-globalization politics. Another non-minor issue is that the technology's relevance does not have a political argument to identify the unfavorable outcomes, and other dimensions of globalization will be used as a scapegoat.

In turn, data is the raw material necessary to fuel AI. The AI fundamentals imply that machine learning, and deep learning improve with more and better data, which means more precise analysis and decisions, that result in a competitive advantage. Data is a non-rival good, it is used by different sources simultaneously, so the challenge is to access the data, not to own it (Varian 2019). Additionally, machine learning, and deep learning methodologies improve with training. Thereby, as companies access new large and complex datasets, the service and product development based on the AI framework will improve. That framework enables the tech companies' expansion into many sectors, creating companies without borders capable of providing services in several industries like AI as a service (AIaaS). Subsequently, the center companies achieve great power while the peripheral countries lag behind, and their companies cannot achieve great results. These arguments confirm our hypothesis that some governments develop the artificial intelligence ecosystem as a national strategy beyond a simple business process.

Our results confirm the relevance of AI in the international system structure, which we contrasted with other metrics, such as additional robustness tests, government expenditure on education as a percentage of GDP, and government expenditure on research as a percentage of GDP. The countries and the new AI leaders were systematically the most consistent in these kinds of public investments, and they have advanced in the number of patents and publications in the science, technology, engineering, and mathematics (STEM) fields. Although some authors argue that the digital nature of algorithms could facilitate the power distribution among many actors, international power does not have the same perspective as other international activities that are consolidated with collective and cooperative schemes, because this power plays a part in strategies of foreign and national security policy. The same is true when the AI ecosystem is a result of different public policies.

Therefore, our findings have some limitations due to the complexity of the international system structure, especially the uncertainty about the evolution of political regimes, the dynamics of public innovation systems in countries that have a consistent framework of artificial intelligence, as well as the investment of companies in those technologies. Additionally, the current model could be limited when the international systems are analyzed from a traditional international identity perspective.

To summarize, artificial intelligence has the potential to change business, society and the economy, but the impact on international power could be most important. We highlight several implications for the structure of the international system in response to advances in AI technology. However, to incorporate technology as an endogenous variable in the study of IR allows us to interpret the future of the international system as a combination of international fitness and technology capabilities. Those factors have been achieved only by some countries with a national ecosystem through public policies of innovation systems, industrial policy, education policy, research and knowledge policies, and foreign policy strategy.

As a consequence, those ecosystems, different features in the quality and quantity of data between the center and periphery countries, as well as AI knowledge, could increase the international power of central countries while the periphery will keep retreating. This would have catastrophic results, as a perpetual state of lag would take place, since they do not have the AI knowledge, and the permanent evolution of other technologies could consolidate the gap between center and periphery. Thus, this research improves the understanding of the international system's dynamic structure and allows us to predict its structural changes in the face of future technological transformation.

This research is exploratory. Future work could integrate several topics. The first would be the role of identity. On the one hand, the logic to identity formation as a part of the culture to consolidate to the artificial intelligence process, and on the other hand, as a part of national identity and its relationship with national interests. Second, multinational corporations (MNCs) are currently the principal developers of AI. Their capabilities are a source of economic and financial power, but they could also involve military and diplomatic power. Thus, could some global tech companies lead to a perpetual lag of periphery countries? Will the companies' role be surpassed by public institutions? How will the relationship between private firms and the state be?

Availability of data and materials

The datasets generated and analyzed during the current study are available in references and from the corresponding author on reasonable request.

Mathematical Appendix

Each new country connects to countries present in the world system and the probability P_i of this connection depends on connectivity k_i influenced by preferential attachment π and fitness η_i (Pham et al. 2016). Thus:

$$P_i = \frac{\eta_i \pi(k_i)}{\sum_j \eta_j \pi(k_j)} \dots (1)$$

If the country does not have these elements, then the probability that it is part of the periphery is high, because not all countries are successful in international influence competitions, they appear at different times and grow at different rates. To simplify, we assume that $\pi(k) = k$, thus, a country will increase its connectivity k_i , at a rate that is proportional to the probability P_i that a new country will attach to it, i.e., each new country of the world system adds μ links to the system (Bianconi and Barabási 2001), following,

$$\frac{\eta_i k_i}{\sum_j \eta_j k_j} = \frac{\eta_i \pi(k_i)}{\sum_j \eta_j \pi(k_j)} \dots (2)$$

The evolution of connectivity $k_i(t)$ established that all countries increase their connectivity in time, mathematically, $k_i(t) = \left(\frac{t}{t_1}\right)^\beta$, where t_i is the period at which country i has been added into the world system and $\beta = \left(\frac{1}{2}\right)$ (Barabási and Albert 1999). Namely, the probability $P(k)$ that a country in the world system interacts with other countries reduces as a power law, given by $P(k) \sim k^{-\gamma}$ (Barabási and Albert 1999).

In other words, countries habitually define their connections from their preferential attachment and other opportunities with their fitness, which means that the time dependence of a country's connectivity depends on the fitness η_i of the country, such that: $k_{\eta_i}(t, t_1) = \mu \left(\frac{t}{t_1}\right)^{\beta(\eta_i)}$, where, t_1 is the time when the country i was included in the world system; $k_\eta = k_{\eta_i}(t, t_1)$; $\beta(\eta)$ is bounded between 0 and 1 because a country increases its links in t , $\beta(\eta) > 0$ and $k_i(t)$ cannot increase faster than t , $\beta(\eta) < 1$. Since $\beta(\eta) < 1$, in $t \rightarrow \infty$ limit $t\beta(\eta)$, can be compared to t and obtain $\lim_{t \rightarrow \infty} (\sum_j \eta_j k_j) = C\mu t (1 + O(t^{-\epsilon}))$, where: $C = \int d\eta \rho(\eta) \frac{\eta}{1-\beta(\eta)}$ and $\epsilon = (1 - \max \beta(\eta)) > 0$ (Bianconi and Barabási 2001). Using these elements, the equation (2) can be written as:

$$\frac{\partial k_\eta}{\partial t} = \frac{\eta k_\eta}{C} \dots (3)$$

which has a solution given by $\eta(\eta) = \eta/C$. To find the connectivity distribution notated by probability $P(k)$ that in this case is a result of a weighted sum over different power laws, namely, the cumulative probability for a certain country $P(k_\eta(t) > k) = t \left(\frac{\mu}{k}\right)^{\frac{C}{\eta}}$ is given by:

$$P(k) \propto \int d\eta \rho(\eta) \frac{C}{\eta} \left(\frac{\mu}{k}\right)^{\frac{C}{\eta} + 1} \dots (4)$$

In the case of a multilayer network, the value $A_{ij}^\alpha = w_{ij}^\alpha$ if the directed link for country j to country i has weight w_{ij}^α , and $A_{ij}^\alpha = 0$ thus, we differentiate between the in-degree $k_i^{in,\alpha}$ and the out-degree $k_i^{out,\alpha}$ of country i in layer α given by:

$$k_i^{in,\alpha} = \sum_{j=1}^N \theta(A_{ij}^\alpha), k_i^{out,\alpha} = \sum_{j=1}^N \theta(A_{ij}^\alpha) \dots (5)$$

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