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Exploring the patterns of international technology diffusion in AI from the perspective of patent citations

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Abstract

This paper presents the findings from a thorough analysis of international technology diffusion (ITD) in artificial intelligence (AI) technologies. We construct a novel framework to explore the patterns of ITD in AI based on patent data published from 1970 to 2019. To this aim, we establish a nexus between *technology innovation (TI) capacity* and *international technology diffusion (ITD) degree*, and divide the countries/regions into three different groups—the leading, middle and backward. Considering the intersecting characteristic of AI technology, this paper examines the ITD patterns in the whole, single-field and intersecting-field AI technology areas. Empirical results show that: (1) Similar patterns are observed in the whole and single-field AI technology. *ITD degree* decreases significantly as *TI capacity* increases in leading countries, while it always remains high though the *TI capacity* improves in backward countries. Middle countries, however, show a transitional state between the two. (2) Compared to the whole AI and single-field AI technology, the pattern of ITD in intersecting-field AI technology is different. The number of nodes in the intersecting-field AI technology has decreased significantly, and the trend is more pronounced in middle and backward countries than in leading countries. These patterns imply that the technological innovation achievements of middle and backward countries will be first identified and utilized by leading countries, which will broaden the growing digital divide between countries and pose a more significant challenge to achieving technological catch-up in the future.

Keywords International technology diffusion · Patent citation · Artificial intelligence (AI) · Network analysis

JEL classification O32 · O57

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Introduction

With the advancement of hardware and algorithms, as well as the generation of massive amounts of data via the Internet, artificial intelligence (AI) has emerged as one of the primary drivers for sustained economic growth. Numerous countries have launched strategic plans for AI, aiming at promote the national innovation capacity of AI technology. Apart from endogenous innovation generated domestically, countries can also acquire technologies from other countries (Eaton & Kortum, 1999; Keller, 2004; Shih & Chang, 2009). As a result, scholars have become increasingly interested in the international technology diffusion (hereafter often referred to as ITD) (Gong & Keller, 2003; Hafner, 2008; Shih & Chang, 2009). Specifically, scholars have been curious about the following questions: How do AI technologies diffuse across countries? What are the patterns of ITD in AI? What do these patterns reveal about the development of AI on a global scale? These are also the central concerns of this paper.

The answers to these questions are critical for the advancement of AI technology. However, as technology is always intangible, either directly tracing the process of ITD or depicting the patterns of it can be difficult in many cases. As a result, the majority of empirical studies are carried out based on patent data, and have depicted the patterns of ITD through patent citation networks (Cho & Shih, 2011; Duguet & MacGarvie, 2005). In a patent document, an inventor must describe the prior art of the invention, which is usually done by citing existing patents or the literature. It is reasonable to assume that technology diffusion has taken place when an earlier patent is cited in an application for a new patent (Globerman et al., 2000). Therefore, patent citations have been noted as a sharp indicator for ITD (Hu & Mathews, 2005; Jaffe & Trajtenberg, 2002). More importantly, the citation relationship between patents has formed a variety of networks, which enables scholars to identify the patterns of ITD by network analysis methods.

According to prior studies, patterns of ITD are identified by networks analysis based on the structural characteristics of international patent citation networks—e.g., size, centrality, density, position, distribution, collaboration, etc. (Hsueh & Wang, 2009; Li et al., 2007; Tsay & Liu, 2020)—of international patent citation networks (Huang & Shih, 2012; Shih & Chang, 2009; Yang et al., 2019). This approach provides a good picture of the interconnections between countries, while it could hardly indicate how "international" a country's technology diffusion is without taking the relationship between domestic and international technology diffusion into consideration. Therefore, it could be difficult to figure out who—domestic agents or international players—benefit more from certain technology innovations from these patterns.

As a complement to the existing approach, this paper constructs a novel framework to explore the pattern of ITD in AI, and this is where we hope this paper makes a contribution. To demonstrate this pattern, we established a nexus between *technology innovation (TI) capacity* and *international technology diffusion (ITD) degree*, and divide the countries/regions into three different groups—the leading, middle and backward. This allowed us to explore how interactions between *technology innovation (TI) capacity* and *international technology diffusion (ITD) degree* vary within different tiers of countries. This also provided an opportunity to develop a refined diffusion pattern rather than carving out a simple global picture in general terms. In addition, considering the intersecting characteristic of AI technology, we examined the ITD patterns in the whole, single-field and intersecting-field AI technology areas. Comparing the ITD patterns of AI single fields as well as intersecting fields, as we believed, could provide deeper insights and inspiration for a more comprehensive understanding of how AI technology diffuses globally.

Theoretical framework, data, and measurement index

This section summarizes the theoretical framework, data, and measurement index of this paper. The theoretical framework elucidates the paper's research concepts and theoretical concerns in detail, while the data and measurement index clarify the research methodology.

Theoretical framework

According to existing research, most AI technology innovation aggregates exclusively in the top countries (Tseng & Ting, 2013), and this has often contributed to aggravate the difference between the countries leading the wave and the rest of the world (Aaronson & Leblond, 2018; Alonso et al., 2020; Horowitz, 2018). This phenomenon is closely related to the inherent characteristics of AI technology. On the one hand, the application of AI technologies relies heavily on the size and quality of data, since it is critical for algorithms training and model optimizing. However, the prominent inequality in Internet penetration (Cruz-Jesus et al., 2018; Ho & Tseng, 2006) and digital infrastructure, such as cloud services, the internet of things (IoT), blockchain, and etc. has resulted in a massive data accumulation imbalance across countries. On the other hand, as an "enabling" technology, the development of AI requires a synergy among science, industry, society and policy (Fujii & Managi, 2018). Particularly, AI creates an emerging ecosystem of innovation that is extremely significant in the interaction between data and application scenarios. For example, with ever more precise AI models in smart medicine, there is an expanding demand on data for medical algorithms training. Meanwhile, the upgraded AI models can serve more complex intelligent medical scenarios by generating more data. As a result, countries with larger intelligent medical scenarios—such as China and the US—possess data with higher quality, which can offer much better solutions than the others.

Considering the above differences that may exist between countries, we have taken an essential step to separate countries into different groups. What is different from prior studies is that we classify countries according to their technology innovation capacity, instead of following the traditional classification, i.e., economic development level (Andrés et al., 2010; Caselli & Coleman, 2001; Hu & Jaffe, 2001; Schiff & Wang, 2006; Seck, 2012), geographic region (Andrews et al., 2015; Eaton & Kortum, 1996; Haruna et al., 2010; Keller, 2002, 2004) or the stage of technological development (Fu et al., 2011; Perkins & Neumayer, 2005; Verspagen, 1991), and the reasons are two-fold. First, technology innovation capacity is inextricably correlated to the patterns of ITD. Studies have shown that ITD has become an important factor that affects economic growth (Huang & Shih, 2012), while successful economic development is intimately linked to a country's capacity to acquire, absorb, disseminate, and apply modern technologies (Metcalfe & Ramlogan, 2008). In addition, the benefits from ITD may vary among countries with different technology innovation capacities (Xu & Chiang, 2005). For example, Comin and Hobijn (2004) implied that countries with stronger technology innovation capacity can benefit more from technology diffusion domestically, because most of the emerging technologies originate and are adopted there first before trickle down to lagging countries. Shih and Chang (2009) also argued that leading countries provide a source of technological knowledge, and latecomers

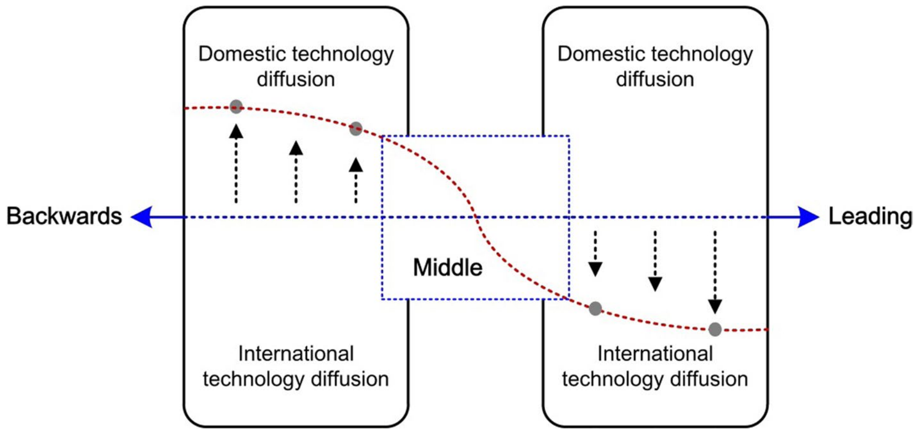


Fig. 1 The theoretical framework of ITD pattern in AI

absorb technological knowledge without reciprocal exportation. Second, in the case of AI, latest technology innovation is primarily driven by application so that countries with huge market demand and high technology innovation capacity can quickly absorb new knowledge from the innovations developed by latecomers, resulting in a reversed technology diffusion from lagging countries to the advanced ones.

Based on the above arguments, we constructed the theoretical framework of ITD pattern in AI with two key elements: first, a classification of countries according to their technology innovation capacity, which is calculated as a basic count of patent publication records by country; second, the relationship between domestic and international technology diffusion. As is shown in Fig. 1, the horizontal line in the framework represents countries' technology innovation capacity in AI and serves as the foundation for our country classification, with backward, middle, and leading countries are listed from left to right. The red curve depicts the ratio between domestic and international technology diffusion of AI in a certain group of countries. What the resulting plotline shows is that, as a country's technology innovation capacity increases, the share of ITD decreases, while the share of domestic technology diffusion increases. The dots depict the condition in a certain country. For example, the first dot on the left side indicates a higher ratio of ITD than domestic diffusion in the specific country.

Data

This study is carried out based on patent publication data retrieved from the Derwent World Patents Index database (DWPI). As one of the most extensively used patent data sources (Huang et al., 2019; Ji et al., 2019; Zhao et al., 2020), the DWPI database contains over 100 million patent documents from over 60 patent-issuing authorities over 36 million patent families. It is widely believed that patents are an important carrier of invention, and that patent citations are crucial indicators of technology diffusion (Chang et al., 2009). Patent citations serve an important legal function since they delimit the scope of the property rights awarded by the patent. Thus, if patent B cites patent A, it implies that patent A represents a piece of existing knowledge upon which patent B builds and over which B cannot have a claim. As Hu and Jaffe (2003) explained, the frequency with which a country's inventors cite the patents of another country is a proxy for the intensity of knowledge flow between the two. In this way, patent citations also reveal the directionality of the knowledge flows, and citations within a country represent domestic technology diffusion.

Based on the domain experts' suggestions, we made the search strategy as shown in the Appendix (Table 1). After removing the duplicate data, we have obtained the AI patent dataset that includes 281,585 patents records published between 1970 and 2019 across five subfields, including natural language process, machine learning, computer vision, expert system, and robots. We deemed this to be a complete and comprehensive picture of AI development globally.

Measurement index

The measurement of technology innovation capacity is also a great matter of interest in related research. The main approach to measuring technology innovation capacity has evolved from a single indicator to a multi-dimensional indicator system since the 1990s, yet patents are one of the most significant indicators that have been broadly used throughout the literature, especially in the context of high-tech sectors (Furman et al., 2002). Since the purpose of this paper is to portray the development and diffusion of AI technology in all relevant countries on a global scale, we selected the most traditional and straightforward method of measuring the technology innovation capacity of AI at the country level, i.e., the number of patent publication records. Therefore, we gauged *technology innovation (TI) capacity* by the total number of AI patent publication records in each country. Although patent counts do not provide a detailed image of a country's capacity for innovation, this is still a commonly used measure (Hu & Mathews, 2005; Johnstone et al., 2010; Suarez-Villa, 1990).

Generally, the frequency with which a given country's inventors cite the patents of another country can be thought of as a proxy for the intensity of knowledge flows from the cited country to the citing country (Hu & Jaffe, 2003). On this basis, we undertake a preliminary attempt to develop a novel indicator for measuring the diffusion of AI technology called *international technology diffusion (ITD) degree* representing the ratio of the number of times that a country's AI patents cited by foreign patents to the total number of citations, i.e., the sum of the number of times that country i's patent cited by domestic patents and foreign patents. This newly developed indicator presents the extent to which a country's technology has spilled over abroad. For each country, the *ITD degree* is calculated as:

$$ITD_i^{\deg ree} = \sum_{j=1}^{n} Ci_j \Big/ \left(\sum_{j=1}^{n} Ci_j + Di\right)$$

where Ci_j indicates the number of times that country i*'s* AI patents are cited by country j, while Di indicates the number of times that country i*'s* AI patents are cited by domestic patents. Therefore, the numerator in the above equation represents the sum of the number of times that country i*'s* AI patents cited by other n countries, and the denominator represents the sum of the number of times that country i's AI patents cited by both domestic and foreign patents.

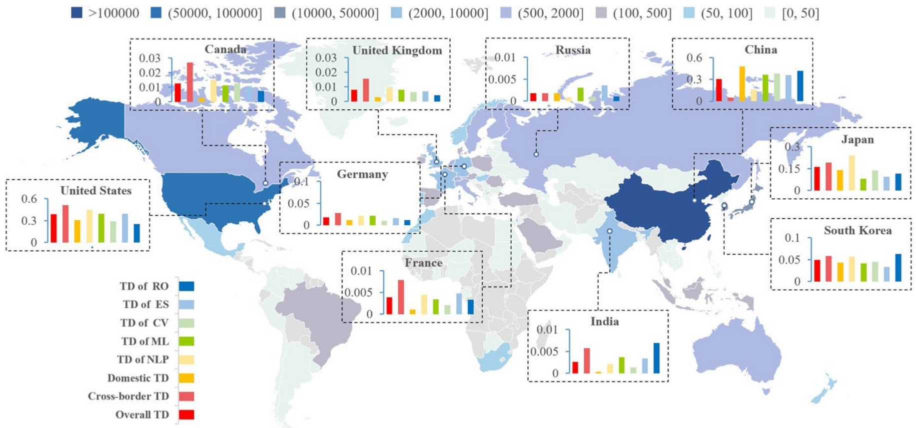


Fig. 2 Global AI technology innovation and technology diffusion for the top 10 countries. *Note* Overall TD is calculated as the sum of the number that a country's (AI) patents cited by both native and foreign patents over the total of all countries. Domestic TD is the number of country's patents cited by native patents citations over the total of all countries. Cross-border TD is the number of country's patents cited by foreign patents over the total of all countries. RO = robotics; ES = expert systems; CV = computer vision; ML = machine learning; NLP = natural language processing

Empirical results

This section concentrates on presenting the empirical results and related analysis of this paper. We first demonstrate basic information on the diffusion of AI technology from spatial and temporal dimensions separately, and then show the empirical results on ITD patterns corresponding to the theoretical framework in terms of the whole AI sector, single-field AI technology and intersecting-field AI technology, respectively.

A global picture of technology innovation and technology diffusion

Figure 2 shows a global picture of *technology innovation (TI) capacity* and technology diffusion in AI. *TI capacity* is reflected in the shade of the country's color, with the darker shades representing higher innovation capacity. China has the highest *TI capacity* in AI, followed by the US, Japan, Korea, then Germany. As *TI capacity* is measured by the total number of AI patents in each country, we believe this may be related to domestic policies such as R&D strategy and subsidy system, which may significantly encourage patent publications in AI. In terms of technology diffusion, we calculate the ratio between the total number of patents cited by other countries for each country to the global total, and the top 10 countries are shown in breakout histograms by overall, domestic, cross-border, and the five subfields. The US has the highest overall technology diffusion, followed by China, Japan, then Korea, which means these countries are the most important contributors to AI knowledge and technology. In addition, we find that China has the highest domestic technology diffusion, followed by the US, Japanese, and Korea, which means that patents in these countries are cited domestically much more frequently than other countries. This, we believe, indicates a more vigorous innovation ecosystem and more active players in these countries. However, compared to high domestic technology diffusion, China has a much lower cross-border technology diffusion. This means that the frequency with which Chinese patents are cited by other countries accounts for a small proportion of global cross-border citations. This could be a side reflection of the fact that Chinese patents are still deficient in terms of global applicability or quality. The same trends tend to hold as we break AI into its different subfields, with the big four still leading in all five areas. However, we also begin to see some areas of specialty emerge between the nations. China leads in basic technology areas like natural language processing and machine learning, while the US appears to excel at applying technologies like computer vision, expert systems, and robotics. Japan is a more prominent performer in natural language processing, while Korea is a prominent performer in robotics. Given each of these countries have different strengths, the scope for ITD will likely continue to expand.

Evolution of AI technology diffusion

One of the great benefits of using citations to track diffusion is that they can also reveal how a country's diffusion patterns have changed over time. Figure 3 shows the diffusion networks decade-by-decade from 1970 to 2019. The first clear observation is that the size and complexity of how AI tech has spread gradually increased over time, with more and more countries being included in the process. The US has always been the world's largest absorber of technological innovation, but their own AI spillover to other countries was not significant until 2000. China became the largest absorber of American AI technology since 2010, and its foreign technology diffusion abroad is far lower than its international technology absorption. This partly illustrates that these two countries have benefitted a lot from ITD. Prior to 2000, the UK, Germany and Canada were the most important diffusers to the US, after then, Japan rose to take leading positions. These countries have experienced a gradual change from technology diffuser to technology absorbers (Table 2).

The ITD pattern of the whole AI sector

Based on the differences in technology innovation capacity, this study roughly divides countries into three groups: the leading, middle, and backward[1]. Figure 4 shows the overall diffusion patterns, and the distinct scatter patterns in each of the three groups, with *TI capacity* on the x-axis and *ITD degree* on the Y-axis. The nodes represent annual *ITD degree* and *TI capacity* values.

Figure 4a demonstrates that the vast majority of countries exhibit both a low *TI capacity* and a high *ITD degree* simultaneously (the scatter plot is distributed in the 2nd, 3rd, 4th quadrants), while the United States, China, Japan, and Korea have shown a quite different evolutionary trend moving towards the bottom right, which sets these four countries apart from others. This phenomenon of these four countries is further analyzed in Fig. 4b, where the logarithmic fit to these four countries is conducted[2]. It is found that, for leading countries in AI (the United States, China, Japan, and Korea), the decreasing *ITD degree*

[1] As shown in Table 2 of the Appendix, we classify countries with more than 10,000 patent publication records as leading countries, countries with 1000 to 10,000 records as middle countries, and countries with less than 1000 records as backward countries.

[2] It should be added that the reason for our logarithmic fit is to intuitively observe the trend and direction of the nodes' evolution over time rather than causal analysis.

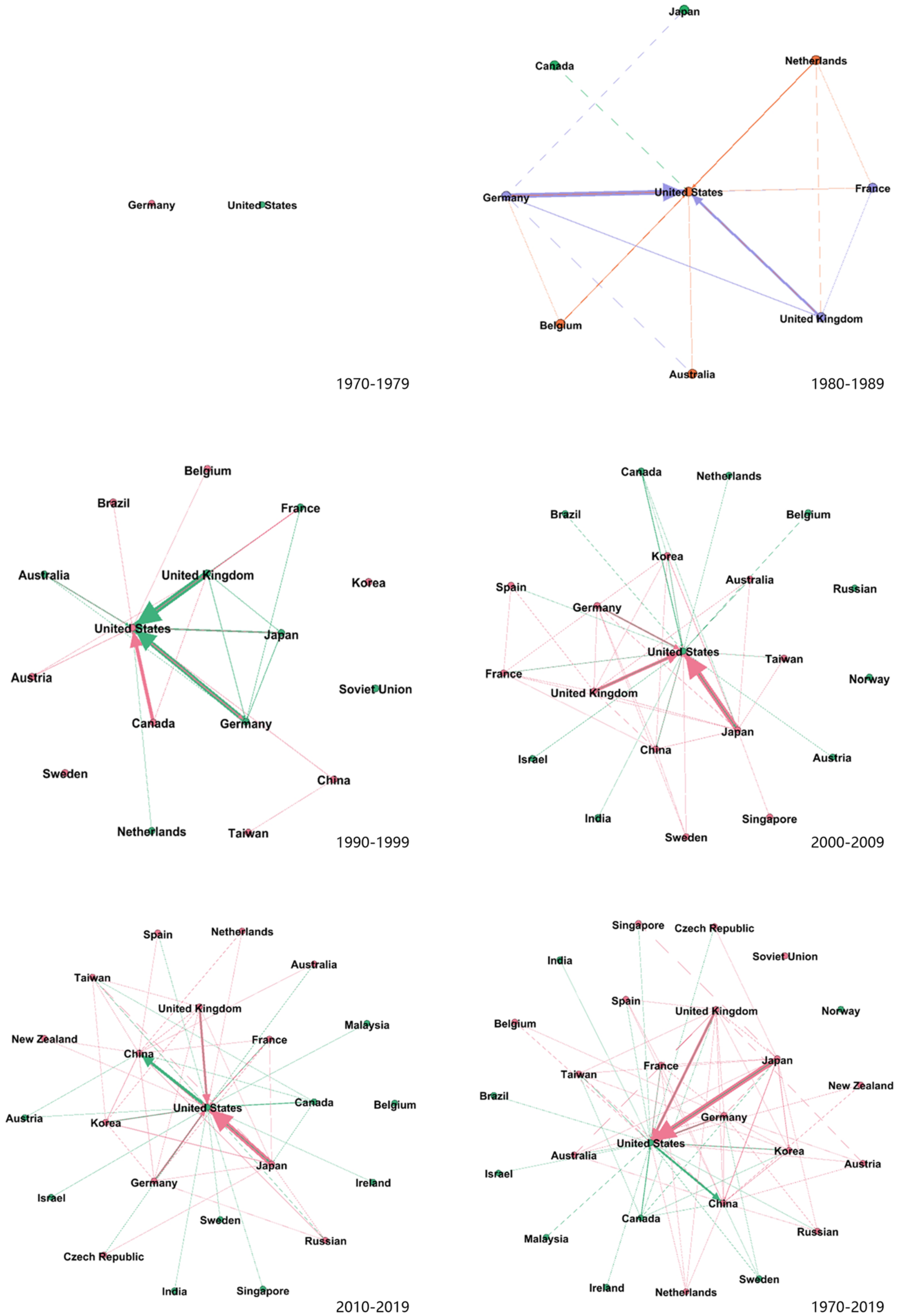
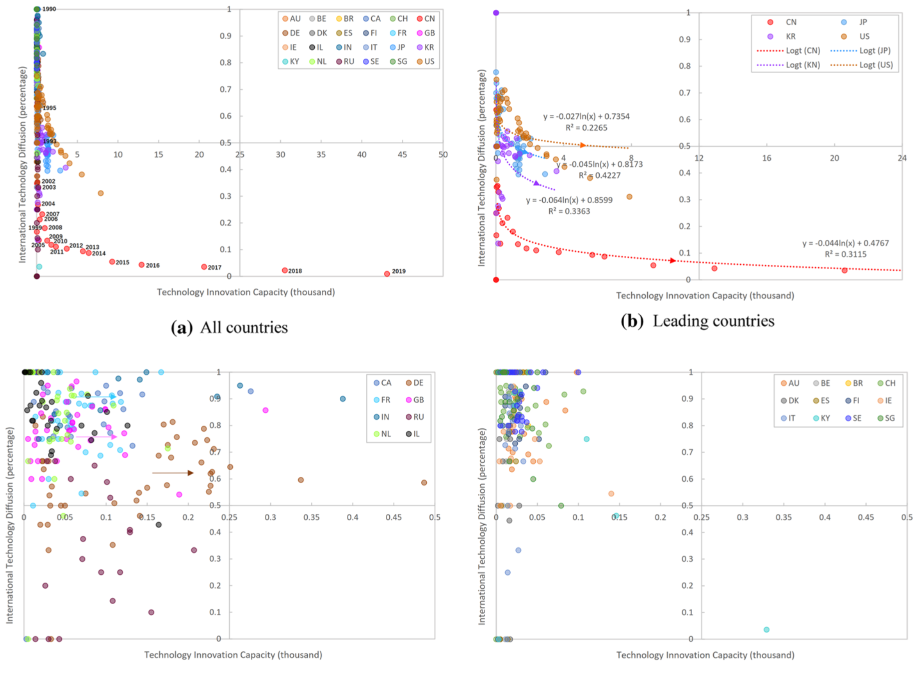


Fig. 3 The evolution of AI technology diffusion



(a) All countries **(b)** Leading countries

(c) Middle countries **(d)** Backward countries

Fig. 4 The ITD pattern of the whole AI sector. *Note* The abbreviation of countries is shown in the legend, and its respective country names are listed in the Appendix

corresponds with the rising of *TI capacity*. Figure 4c focused on middle countries (i.e., the countries with lower *TI capacity* compared with leading countries) and countries mainly scattered in the 2nd quadrant and has shown a tendency of moving towards the right gradually. Figure 4d illustrates the case of backward countries, which, unlike Fig. 4c, have their scatters clustered in the upper left corner of the 2nd quadrant. The empirical results in Fig. 4 show that for leading countries (e.g., the United States, China, Japan, Korea), there is a logarithmic curve relationship between *TI capacity* and *ITD degree*, and their scatter plot appears to congregate towards the 4th quadrant; for middle countries, the scatter plot tends to be dispersed in the 2nd and 3rd quadrant, while backward countries gathering more towards the top left corner. This gives basic evidence for the proposed pattern in the theoretical framework.

The ITD pattern of single-field AI technology

To further explore and cross-check this pattern, we separately examined diffusion pattern for single-field technologies (i.e., AI technologies that involve only one sub-field, such as natural language processing) versus those intersecting-field technologies (i.e., AI technologies that

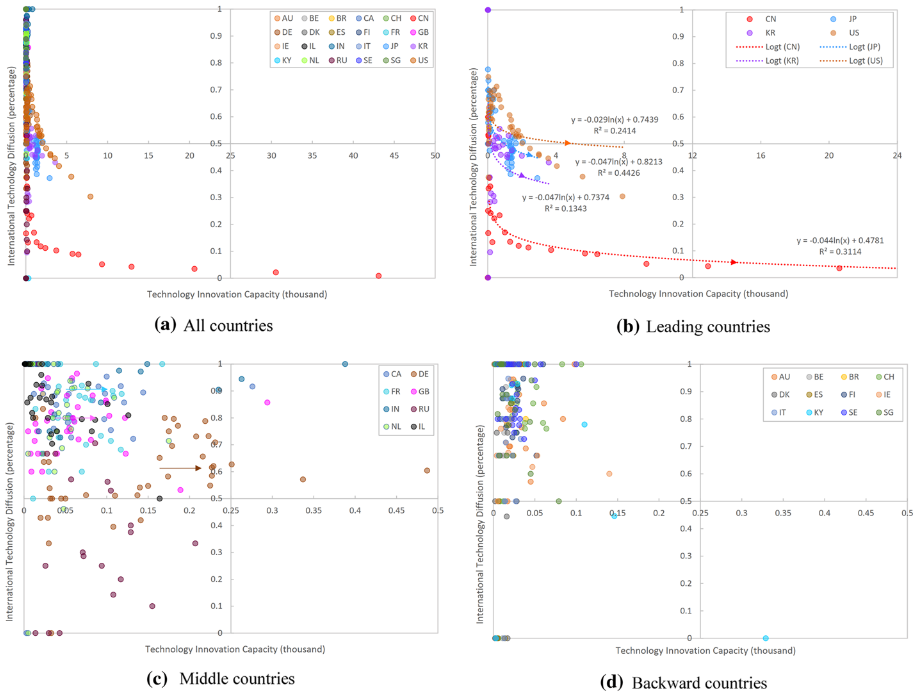
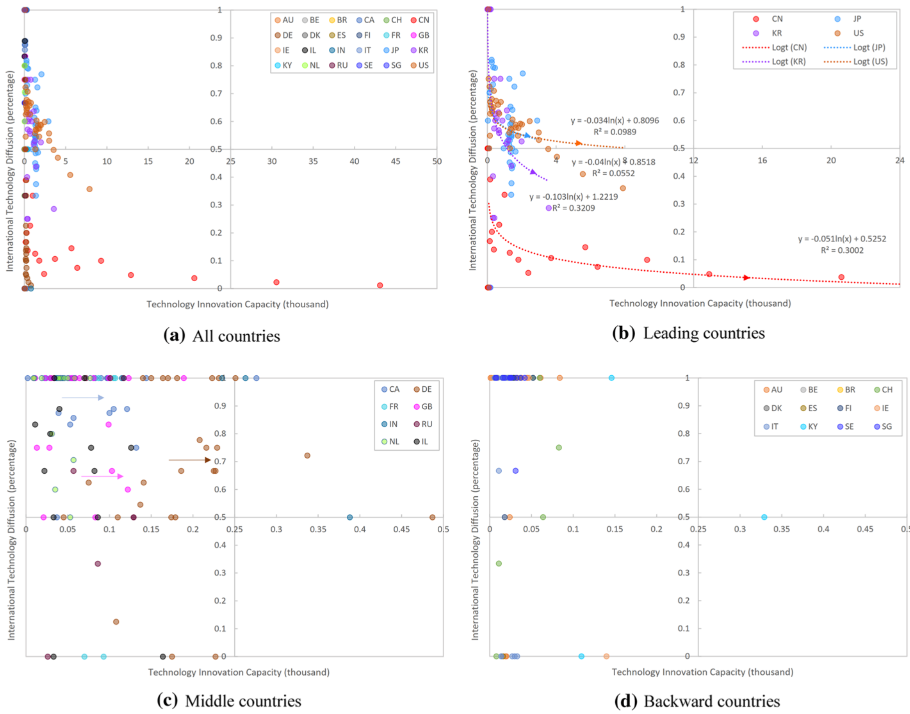


Fig. 5 The ITD pattern of the single-field AI sector. *Note* The figure sums up the technological diffusion of five single-field AI technologies and does not refer to a specific technology alone

involve at least two sub-fields, such as expert systems and machine learning). It was our conjecture that we would not see as much diffusion in the intersecting-field technologies because they tend to be more complex. The results of the analysis for the single-field technologies appear in Fig. 5.

As is shown in Fig. 5 (a, b, c, d), the pattern in single-field AI technology is quite in accordance with the pattern in whole AI technologies for all groups of countries, with the logarithmic curve and scattering plot basically remain the same. This pretty much means that the ITD pattern we found in the whole AI sector is validated in single-field AI technology. However, the situation in leading countries shows a slight difference. It is illustrated in Fig. 5b that although the trend of the logarithmic curves remains consistent with its counterpart in the whole AI sector, which reveals that the decreasing *ITD degree* corresponds with the rising of *TI capacity*, the *ITD degree* in single-field technology is declining slightly more rapidly than that in the whole AI sector. For middle countries and backward countries, the pattern of ITD in a single-field technology is essentially the same as that in the whole AI sector, where the lower a country's *TI capacity*, the more its scatter plots congregate in the 2nd quadrant. At the same time, differences in ITD patterns between middle countries and backward countries remain significant, as shown in Fig. 5c and d. Middle countries are scattered in the 2nd quadrant and have shown a tendency of moving towards the right gradually, while backward countries have their scatters clustered in the upper left corner of the 2nd quadrant. The similar patterns of ITD exhibited in the single-field technology and the whole AI sector suggest that ITD in AI is still dominated by the diffusion of single-field



(a) All countries **(b)** Leading countries

(c) Middle countries **(d)** Backward countries

Fig. 6 The ITD pattern of the intersecting-field AI sector

technology. Even though intersecting-field AI technology may show differentiated pattern, they still do not have a decisive impact on the overall ITD pattern in AI.

The ITD pattern of intersecting-field AI technology

Generally, the pattern of ITD in intersecting-field AI technology is largely consistent with that in the whole AI sector and single-field AI technology. However, there are some noteworthy new changes in ITD pattern of intersecting-field. Trends occurring along with different groups of countries in terms of the intersecting-field AI technology are then illustrated in Fig. 6.

Specifically, Fig. 6b shows that for leading countries, the trend of ITD in intersecting-field AI technology is much less clear than that of the whole AI sector and single-field technology equivalents. For example, it is difficult for us to even fit a logit to the ITD in Japan. Moreover, as shown in Fig. 6c and Fig. 6d, there are differences between intersecting-field AI technology and the whole AI sector as well as single-field AI technologies. First, the total number of scatter plots is limited, and the proportion of scatter plots equal to 1 is higher than that in the whole AI sector as well as in single-field AI technology. It can be seen that the tendency for countries to congregate in the 2nd quadrant is fading. Second, for middle countries, the number of nodes is substantially fewer in the 2nd quadrant, with the majority of them clustered there, while countries that were previously in Fig. 5c's 3rd quadrant (e.g., Russia) nearly vanish in Fig. 6c. This implies an insufficiency in technology innovation and international influence in the intersecting-field technology compared to single-field technology. Third, for backward countries, the *ITD degree* shows a more pronounced polarization trend. In the whole AI sector and in single-field technology, the *ITD degrees* of backward countries are largely evenly distributed on the left side of the 2nd quadrant; however, in intersecting-field AI technology, significantly fewer countries are located in the middle, with most countries having either a 0 or a 1 in terms of *ITD degree*. This means that backward countries contribute little to ITD in intersecting-field AI technology, and their technological innovations are more often exploited by other countries.

Conclusion and discussion

As AI technology advances, research on how it is spreading across the globe is becoming more prevalent. This paper, however, is the first to focus on technology diffusion patterns from the perspective of the relationship between technology spreads domestically and internationally. To this end, we developed a new indicator called the *international technology diffusion (ITD) degree*, that reflects the proportion of a country's total diffusion that is international. With this indicator, we measured precisely how "international" a country's technology diffusion is, contributing to a deeper understanding of technology diffusion at both the domestic and international levels. Based on patent data retrieved from the DWPI database, we were able to clearly demonstrate the divergence between countries by dividing them into three groups—leading, middle and backward—according to their technology innovation capacity, for technology diffusion and technology adoption in AI is more strongly related to a country's technology innovation capacity. Further, we also take the prominent intersecting characteristics of AI technologies into consideration and providing a pioneering finding on the divergent diffusion patterns between single-field AI technologies and intersecting-field technologies, supplying inspiration for a more comprehensive understanding of the patterns of ITD in AI. The main conclusions and further discussion are as follows.

First, by portraying the spread of AI on a global scale and comparing countries from different groups, we found a new basic pattern of ITD. Within this pattern, there is an obvious trend of polarization, where China, the US, Korea, and Japan are currently leading the stakes, while other countries have been drawn into a passive process of diffusion, especially backward countries. More specifically, for leading countries, the *ITD degree* decreases as *TI capacity* increases. For middle countries, *TI capacity* has been gradually increasing over the period, but *ITD degree* has not decreased to the same relative proportion as with leading countries. It shows a more transitional state between that of leading countries and backward countries. For backward countries, *TI capacity* has not significantly increased, but the *ITD degree* remains high. This pattern indicates that the technological achievements of middle and backward countries are being identified and used by leading countries, rather than being spread domestically, which is contrary to the findings of existing research that technology diffuses much more slowly between countries than within them (Eaton & Kortum, 1999; Huang & Shih, 2012). Moreover, for middle and backward countries, the high *ITD degree* reveals that AI innovation clusters have not been formed to allow the country to rapidly absorb new knowledge. Rather, it appears these clusters lack the ability to harness their innovations for domestic use.

Second, this pattern holds as we examine the whole AI technology and single-field technologies but not completely with intersecting-field technologies. Specifically, the number of nodes in the intersecting-field technology pattern has decreased significantly, a trend that is more pronounced in middle and backward countries than in leading countries. Moreover, there are even some countries that have almost disappeared, such as Russia. The reasons behind this change deserve further consideration. Our preliminary view is that intersecting-field technologies tend to be more complex and more cutting-edge than single-field technologies. It is likely that only a few companies with significant positions in the global AI market and a few institutions with leading levels of AI research have the demand and ability to develop and apply innovations that span multiple subfields. As a result, such technological innovations will first spread to the global leaders in AI. However, it is difficult for national-level studies to reveal the mechanisms behind this phenomenon, and we need to look for answers from a more microscopic dimension in the future.

On the basis of these conclusions, we believe that the reasons for the patterns of ITD identified in this paper deserve further discussion. First, each country's domestic institutional and policy environment may exert great impacts on the ITD patterns of AI. Studies show that R&D strategies, industry policies like subsidies, financial policies, and intellectual property protection systems may have a significant impact on patenting behaviors and ITD (Agrawal et al., 2019; Fujii & Managi, 2018; Wang & Siau, 2018). According to the empirical results, the overall ITD of China and the US is very similar, i.e., the *ITD degree* is significantly low in both countries. However, there may be distinct reasons for the resemblance. For instance, in the context of technological catch-up, China's patenting system, government subsidies, and other policies may have resulted in a significant increase in the number of patent applications, but only a small proportion of these patents may be of high quality. Consequently, few other countries may deem Chinese patents worthy of citing. By comparison, US innovation policies and a thriving capital market should be encouraging high levels of innovation. However, the innovation level in the US may be so high that other countries find it difficult to absorb and exploit the technological breakthroughs made in the US, at least on a timely basis. Therefore, to fully understand international diffusion patterns, there is a need to analyze a country's underlying domestic institutional and policy factors. Second, this ITD pattern can also be affected by the characteristics of key elements in AI, such as data. It has been noted that a virtuous ecological cycle between data, technology, and the market is being formed in leading countries (e.g., the United States and China), but middle and backward countries have obvious disadvantages in this regard. In fact, the most important reason for this phenomenon is that data has become a new and particularly important factor of production in the field of AI. Data's unique characteristics mean that countries with more data are finding it much easier to innovate. Thus, the nature of data itself is a fundamental contributor to the growing digital divide between countries. Without redress, data paucity may, in the future, pose great challenges to achieving technological catch-up for some countries.

There are still some limitations in this paper. First, our new indicator only reveals the situation that a country's AI technology innovation is being identified and absorbed by other countries while does not capture its absorption of foreign technologies. Whether this leaves a gap in the literature or is the right choice because it reduces confusion and prevents double counting remains to be explored. Second, while we have identified ITD patterns in AI with completely new indicators, we have not rigorously analyzed the reasons for the formation of these patterns. In fact, this would be a topic with very policy implications. These issues will be left to future studies.

Appendix

See Tables 1 and 2

Table 1 Search strategy for AI patents

Category	Search strategy	Amount
Machine learning	ABD = ((Artificial Intelligence) OR (Machine Learn*) OR (Deep Learn*) OR (Inductive Learn*) OR (Memory Based Learn*) OR (Reinforc* Learn*) OR (Statistical Learn*) OR (Automat* Theorem) OR (Decision* Tree*) OR (Evolution* Algorithm*) OR (Genetic Algorithm*) OR (Particle Swarm Optimiz*) OR (Algebraic Graph*) OR Metareason* OR ((Abductive OR Analogical OR Bayesian OR Case* OR (Case* Based) OR Commonsense OR (Common Sense) OR Constraint OR (Constraint Based) OR Diagrammatic OR Graphic OR Logic OR Meta OR Qualitative OR (Rule Based) OR Spatial) ADJ1 (Inferenc* OR Reason*)) OR (Situation* Calculus) OR (Response Surface Method*) OR (Graph Theory) OR (Adaptive Control*) OR (Adaptive Critic) OR (Adaptive Heuristic Critic) OR (Adaptive Dynamic) OR (Adaptive Fuzzy Control*) OR (Adaptive Neural Control*) OR (Artificial Neural Network*) OR (Non-Monotonic Logic*) OR (Nonmonotonic Logic*) OR (Description Logic*) OR (Fuzzy Logic*) OR (Evolution* Comput*))	25,643
Computer vision	ABD = ((Computer* Vision*) OR (Machine Vision*) OR ((Handwrit* OR Image* OR Picture* OR Face* OR Pattern* OR Video*) ADJ1 (Identification* OR Recognition*)) OR (Gesture* Control*))	35,912
Natural language process	ABD = ((Feature* Extract*) OR (Semantic Network*) OR (Semantic Web) OR (Sparse Represent*) OR (Acoustic Process*) OR (Machine Translat*) OR (Natural Language Process*) OR (Natural Language Understand*) OR ((Speech OR Voice) ADJ1 (Recognition* OR Identification* OR Synthesis OR Translat*)) OR (Heuristic Search*) OR ((Text Summar*) OR (Text Digest*)))	42,062
Expert system	ABD = ((Expert* System*) OR (Decision* Making*) OR (Backstepping Design*) OR (Belief Revision*) OR ((Backstepping OR Boundary OR Containment OR Cooperative OR Coordination OR Collaborative OR Decentralized OR Distributed OR (Dynamic Surface)) ADJ1 Control*) OR (Fuzzy ADJ2 Control*) OR (Fuzzy Logic System*) OR ((Automated OR Intelligent OR Smart) ADJ1 (Grading OR Tutoring OR Scoring OR Coaching)) OR ((Intelligent OR Smart) ADJ1 (Planning OR Scheduling OR (Problem Solving) OR (Problem Solving) OR (Question* Answer*) OR system *)) OR (Artificial Life))	20,807
Robot	ABD = (((Autonomous OR Humanoid OR Intelligent OR Smart) ADJ2 Robot*) OR (Bio-robot* OR (Bio* ADJ2 Robot*) OR Bio robot*) OR (Robot* ADJ1 (Cognition* OR Percept* OR Sens* OR Plan* OR Schedule*)))	6999

Table 2 Countries/regions and their country code

Number	Country/Region	Country Code	Records	Number	Country/Region	Country Code	Records
1	China	CN	140,746	13	Switzerland	CH	811
2	United States	US	52,923	14	Sweden	SE	765
3	Japan	JP	38,930	15	Cayman Islands	KY	733
4	South Korea	KR	18,173	16	Australia	AU	718
5	Germany	DE	6452	17	Finland	FI	539
6	India	IN	2412	18	Italy	IT	511
7	United Kingdom	GB	2209	19	Singapore	SG	463
8	France	FR	2061	20	Ireland	IE	447
9	Canada	CA	1927	21	Spain	ES	439
10	Russia	RU	1716	22	Brazil	BR	395
11	Netherlands	NL	1281	23	Belgium	BE	237
12	Israel	IL	1092	24	Denmark	DK	205

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Declarations

Conflict of interest The author declared that there is no conflict of interest.

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