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Integrating Artificial Intelligence into Regional Technological Domains: The Role of Intra- and Extra-Regional AI Relatedness

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Abstract:

Artificial intelligence (AI) is a key driver of the Fourth Industrial Revolution. Despite growing interest in the geography of AI, our understanding of how AI integrates into regional contexts remains limited. In response, we examine the integration of AI into regional technological domains in China and the United States using patent data. Theoretically, we develop a framework by introducing the concepts of intra- and extra-regional AI relatedness. Our findings reveal that the integration of AI into regional technological domains is positively associated with both intra-regional and extra-regional AI relatedness. Additionally, extra-regional AI relatedness can moderate the lack of intra-regional AI relatedness.

Key words*:* integration of artificial intelligence, intra-regional AI relatedness, extra-regional AI relatedness, regional technological domains, China, the United States

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Introduction

Historically, industrial revolutions have been driven by megatrends linked to the emergence and subsequent integration of new technologies into the broader economy. The First Industrial Revolution was fueled by steam power, the Second by electricity, and the Third by information and communication technologies (Bresnahan & Trajtenberg, 1995; Petralia, 2020). More recently, artificial intelligence (AI) - defined as a machine-based system capable of performing tasks that typically require human intelligence, such as make predictions, recommendations, and decisions (Russell & Norvig, 2009; Furman & Seamans, 2019; OECD, 2019; WIPO, 2019) - is expected to drive the Fourth Industrial Revolution (Schwab, 2017). This is not only due to AI being an emerging technology but also because it has the potential to significantly change the pace and direction of economic progress as a general-purpose technology (GPT) [1] (Trajtenberg, 2019; Haefner et al., 2021).

Against this backdrop, the geography of AI has gained increasing attention from both policy circles (European Commission, 2018) and in the field of evolutionary economic geography (Buarque et al., 2020; Doloreux & Turkina, 2021; Lazzeretti et al., 2023; Xiao & Boschma, 2023; Rodríguez-Pose & You, 2024). To date, researchers in this field have examined the emergence of AI technology in regions (Doloreux & Turkina, 2021; Xiao & Boschma, 2023) and its role in regional innovation (Cicerone et al., 2023; Rodríguez-Pose & You, 2024). For instance, Xiao & Boschma (2023) studied the emergence of AI technologies in European regions from 1994 to 2017; Rodríguez-Pose & You (2024) explored the impact of AI and robotics on technological innovation in Chinese cities.

However, the literature in evolutionary economic geography has yet to fully address the integration of AI into regional technological domains, especially considering AI's role as a general-purpose technology. While Buarque et al. (2020) have explored the integration of AI into the knowledge space of European regions, their analysis remains focused at the regional

[1] GPT is defined as 'a single generic technology, recognizable as such over its whole lifetime, that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects' (Lipsey et al., 2005, p. 98)

level. In reality, regional knowledge encompasses diverse technological domains, each of which integrates AI to varying degrees. Therefore, it is crucial to extend this investigation to the integration of AI into specific regional technological domains. Here, we define the integration of AI into regional technological domains as the incorporation and application of AI technology into a particular regional technological domain, inspired by the definition of the integration of AI in regional knowledge space (Buarque et al., 2020). We further argue that this area deserves greater scholarly attention, not only due to its under-examination but also because of AI's practical potential to significantly enhance productivity and stimulate regional economic growth (Agrawal et al., 2019; Trajtenberg, 2019). For example, in the pharmaceutical and medical technology domain, AI has been integrated into drug discovery, protein folding analysis, and the investigation of biological processes. According to McKinsey (2023), AI could boost productivity by 2.6 to 4.5 percent of the industry's annual revenues, equating to an additional $60 billion to $110 billion.

This raises the question of what factors influence the integration of AI into regional technological domains. Since a region's ability to integrate AI into a specific regional technological domain depends on its capability to absorb AI technology, the concept of relatedness in evolution economic geography provides a valuable starting point. Traditionally, relatedness measures the cognitive proximity of a given technology to the existing portfolio of technologies within a region, suggesting that greater relatedness facilitates easier absorption (Neffke et al., 2011; Hidalgo et al., 2018). While insightful, this conventional understanding of relatedness is too broad to accurately capture the likelihood of absorbing and integrating AI technology. This is because what is crucial for AI integration is not the capability to absorb any technologies (i.e., the conventional relatedness) but specifically AI technology (i.e., AI relatedness). Here, AI relatedness measures how close a given technological domain is to the existing portfolio of AI technologies in regions. Moreover, some regions, especially less developed ones, often lack sufficient AI relatedness and, therefore, need to access AI relatedness from other regions. To address this, we combine the concept of (intra-regional) AI relatedness with the role of complementary inter-regional linkage (Balland & Boschma, 2021), introducing the concept of extra-regional AI relatedness, which refers to the extent to which a region can access AI relatedness from other regions.

In brief, this article examines how intra- and extra-regional AI relatedness influence the integration of AI into regional technological domains. We construct a panel dataset using patent data from the China National Intellectual Property Administration (CNIPA) and the United States Patent and Trademark Office (USPTO) for the period 2001-2020. The econometric analysis, using a linear probability model (LPM), reveals that the integration of AI into regional technological domains is positively associated with both intra- and extra-regional AI relatedness. Furthermore, we find that extra-regional AI relatedness can moderate the lack of intra-regional AI relatedness.

Our study makes two contributions. First, while the literature on the geography of AI has increased, few studies have examined the integration of AI into regional technological domains. Building on Buarque et al.'s (2020) work, which investigates AI integration in regional knowledge base in the EU, this article advances the discussion by providing a more granular analysis of AI integration – moving from the regional level to the regional technological domain level. Second, to explain the integration of AI into regional technological domains, we introduce the novel concept of AI relatedness and extend it to both intra- and extra-regional levels. Unlike conventional relatedness, AI relatedness is tailored to the integration of AI, as it specifically measures how close a given technological domain is to the existing portfolio of AI technologies in a region, rather than to non-AI technologies.

The remainder of the paper is structured as follows. Section 2 presents the literature review and hypotheses. Sections 3 describes the data, variables, and econometric model. Section 4 discusses the main results. Section 5 concludes the paper.

Literature review and hypotheses

Not all technologies are integrated into the economy to the same extent. What sets AI apart is its ability to be pervasively applied across a wide range of sectors (Agrawal et al., 2019;

Trajtenberg, 2019), distinguishing it from other technologies that are limited to specific areas (Harada, 2009). This widespread integration stems from AI's nature as a general-purpose technology. So far, the integration of AI at the firm-level has been explored in management studies literature (DeStefano et al., 2022; Dahlke et al., 2024). However, research on AI integration from a geographical perspective remains limited (Buarque et al., 2020; Lazzeretti et al., 2023). A notable contribution int this area is Buarque et al. (2020), who examined AI integration at the regional level, focusing on how AI integrates with the knowledge space of European regions. However, since regional knowledge includes various technological domains, each with its own level of AI integration, there is a need for a more detailed examination of AI integration at the level of regional technological domains.

In below, we explore the geographical determinants of the integration of AI into regional technological domains. Drawing on the concepts of relatedness (Neffke, et al., 2011; Hidalgo et al., 2018) and complementary inter-regional linkage (Balland & Boschma, 2021), we introduce the concepts of intra- and extra-regional AI relatedness, tailored to the specific context of AI integration. Our framework posits that the integration of AI into regional technological domains depends on region's ability to access and absorb AI technologies both within the region and from external regions (i.e., in terms of intra- and extra-regional AI relatedness). Moreover, we highlight that the lack of AI relatedness in regions can be moderated by accessing extra-regional sources.

Intra-regional AI relatedness and the integration of AI into regional technological domains

A key prerequisite for integrating AI into regional technological domains is a region's capability to perceive and access AI technology; without this, integration cannot occur (Rogers, 2003). The successful integration of AI is thus conditioned by a region's ability to access AI technology both from within and outside the region. Typically, regions prioritize geographically local searches for AI due to the constraints imposed by geographical distance between AI adopters and providers (Boschma, 2005; Boschma & Frenken, 2010). Empirical evidence at the firm level supports this, indicating that the effectiveness of integrating AI generally decreases as the geographical distance increases (Jaffe et al., 1993; Dahlke et al., 2024). Consequently, regions are more likely to integrate AI that originates from their own region.

Yet, the presence of AI in the regions is only a necessary but insufficient condition for successful AI integration. Effective AI integration also depends on region's absorption capacity. For successful integration, there must be a certain degree of cognitive proximity between the region's preexisting technological base and AI technologies (Nooteboom 2000; Boschma, 2005). If AI technologies is too distant from the region's preexisting technological bases, the learning cost will be high, making it difficult for the region to effectively learn and integrate AI technologies (Boschma, 2005).

In sum, the integration of AI into regional technology domains depends not only on the regional stock of AI (i.e., geographical proximity), but, more importantly, on the cognitive proximity between a region's preexisting technological bases and AI technologies. This combination of proximity dimensions is captured by the concept of relatedness, which measures how close or distant a given technology is to the portfolio of technologies in a region (i.e., both the blue circles and orange squares in Figure 1) (Neffke et al., 2011; Hidalgo et al., 2018). To tailor this concept of relatedness to the specific context of AI integration, we introduce the concept of AI relatedness, which specifically measures how close or distant a given technology and the stock of AI technology in a region (i.e., only the blue circles in Figure 1).

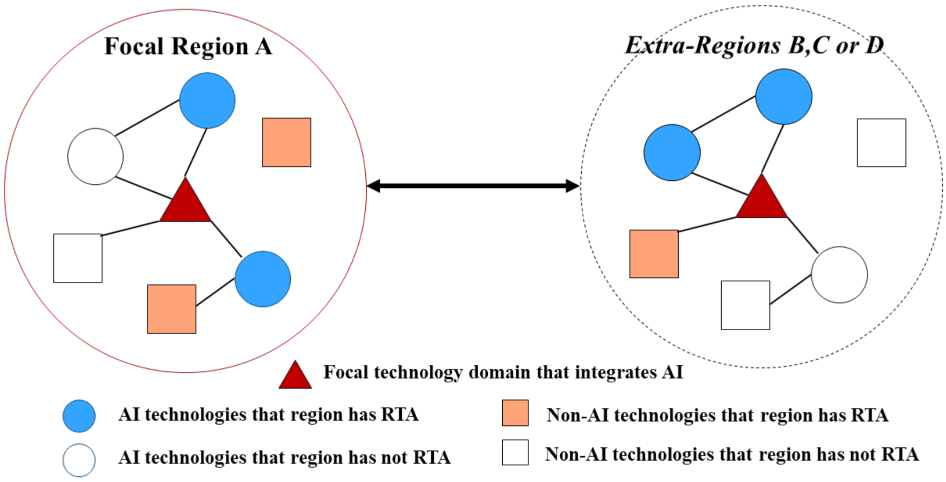

Figure 1. The framework of integrating AI into regional technological domains.

Compared with the conventional concept of relatedness, AI relatedness more accurately captures regional capabilities to absorb and integrate AI technologies in three ways. First, the conventional concept of relatedness was designed to explain regional capabilities for *developing* a given technology *per se*, rather than for *integrating it with other technologies*, such as AI. For example, the highly cited paper by Balland et al. (2019) used the concept of relatedness to examine regional capabilities to develop 33 new technologies in 282 NUTS-2 regions in Europe, but not the regional capabilities to integrate these technologies with others, such as AI. Second, the conventional concept of relatedness is too broad to effectively capture a region's ability to integrate AI, as it includes both AI relatedness and non-AI relatedness. In contrast, AI relatedness focuses specifically on regional capability to integrate AI, filtering out capabilities that are unrelated to AI. This refinement is supported by management literature; for example, Rahmati et al. (2021) found that a firm's digital proximity (i.e., the relatedness between firm's preexisting technology stock and the digital technologies, including AI), rather than firm's proximity in general, facilitates the integration and adoption of digital technologies. Similarly, a study on the integration of AI in China's financial sector shows that AI integration is positively associated with the local stock AI technologies relevant to finance (Dai & Chen, 2022). Third, the role of non-AI relatedness in AI integration is uncertain. On the one hand, non-AI relatedness might hinder AI integration due to its cognitive distance from AI or the potential for AI to replace non-AI technologies (Acemoglu & Restrepo, 2018). On the other hand, there might be complementarities between AI and non-AI skills, as the integrating AI into a specific domain might require some domain-specific knowledge (Chen, 2021). In sum, by focusing on AI-related capabilities, AI relatedness offers a finer-grained understanding of regions' ability to integrate AI technologies. Based on these discussions, we propose the following hypothesis:

Hypothesis 1: The integration of AI into regional technological domains is positively associated with the intra-regional AI relatedness.

Extra-regional AI relatedness and the integration of AI into regional technological domains

However, region often do not *ex ante* possess all the AI technologies needed for integration into a specific regional technology domain. In order to gain access to these AI technologies, which are lacking in the regions, regions usually establish extra-regional linkages to compensate for this (Balland & Boschma, 2021; Chen, 2022). So far, studies have found that inter-regional linkages play a positive role in regional innovation and technological diversification (De Noni et al., 2017; Barzotto et al., 2019; Santoalha, 2019). These linkages allow regions to benefit from non-local knowledge inputs, which provide supplement external knowledge with local knowledge (Bathelt et al., 2004). For example, Barzottoa et al. (2019) found that inter-regional collaboration fosters regional innovation. Similarly, Santoalha (2019) posits that cooperation both within and across regions significantly boosts regional diversification in Europe.

Yet, most of the above studies have primarily focused on the intensity of extra-regional linkages, rather than their specific characteristics (Balland & Boschma, 2021; De Noni & Ganzarolib, 2023). In response, recent studies have begun to explore the different types of inter-regional linkages and their distinct roles. The first strand looks at the variety of extra-regional linkages, considering both geographical and technological aspects. For example, Kogler et al. (2023) found that extra-regional linkages involving a diverse range of regions contribute to regional diversification, especially unrelated regional diversification. Similarly, De Noni & Ganzarolib (2023) demonstrated that both geographical and technological extra-variety matter for regional innovation. The second strand differentiates extra-regional linkages based on the degree of relatedness between a region's existing technologies and the technologies from extra-regional sources. For example, Miguelez & Moreno (2018) found that extra-regional linkages promoted radical innovations when the extra-regional knowledge is related to, but not identical with, the region's existing knowledge base. The third strand combines both the variety and relatedness of extra-regional linkages to develop a new indicator of complementary inter-regional linkage. This indicator measures the extent to which a set of extra-regional linkages can provide related capabilities that are missing in a region (Balland & Boschma, 2021). Evidence from European regions indicates that such complementary inter-regional linkage can enhance a region's ability to diversify into new technologies (Balland & Boschma, 2021). Similar results were observed in the emergence and development of digital and green technology across Europe regions (Bachtrögler-Unger et al., 2023).

Building on the concept of complementary inter-regional linkages and the notion of AI relatedness, we introduce the concept of extra-regional AI relatedness. This concept measures how close or distant a given technology in a region is to the AI technologies present in a set of extra-regions that are connected. We expect that extra-regional AI relatedness matters for the integration of AI into regional technological domains. This is because a diverse set of extra-regional linkages provides opportunities to combine distinct pieces of knowledge and to come up with innovative ideas (Bathelt et al., 2004; Kogler et al., 2023). Additionally, cognitive proximity enhances the likelihood that region can successfully absorb and integrate AI technology (Boschma, 2017; Hidalgo et al., 2018). This understanding is exemplified by a case study on the digitalization of financial sector in Shenzhen, China, which found that acquiring extra-regional AI technologies related to finance played a crucial role in accelerating the integration of AI into regional financial domain (Chen, 2021). Based on these above discussions, we hypothesize the following:

> *Hypothesis 2: The integration of AI into regional technological domains is positively associated with the extra -regional AI relatedness.*

The interaction between intra- and extra-regional AI relatedness

Although both intra- and extra-regional AI relatedness are important (De Noni et al., 2021), their relationship is far from clear in existing studies. Most studies indicate that accessing extra-regional capabilities can moderate the lack of intra-regional capabilities (Miguelez & Moreno, 2018; Neffke et al., 2018; De Noni et al., 2018; Kogler et al., 2023). In other words, regions that lack necessary intra-regional capabilities can still innovate if they are able to interact appropriately with the missing capabilities beyond their regional borders and combine these interregional capabilities with their absorptive capacity. For example, Kogler et al. (2023)

found systematic evidence in Europe that inter-regional networks can compensate for the lack of a local pool of related technological knowledge, particularly through the rate, diversity, and intensity of external collaboration. This compensatory effect is often more common in peripheral regions, which often have limited capabilities. Grillitsch & Nilsson (2015) support this view, demonstrating that acquiring extra-regional capabilities is crucial for innovation in peripheral regions due to their inherent capability limitation. However, not all studies support this negative moderating role of extra-regional capabilities, some studies find a reinforcing relationship between intra- and extra-regional capabilities. For example, Balland & Boschma (2021) found that extra-regional linkages can reinforce the effect of intra-regional relatedness on technological diversification in regions, based on a study of 292 NUTS-2 regions in Europe.

Take the AI integration in China as an example, we expect that extra-regional AI relatedness can moderate the lack of intra-regional AI relatedness. Similar to Europe (Xiao & Boschma, 2023), AI technologies in China are geographically concentrated in developed regions (Rodríguez-Pose & You, 2024). Yet, as AI continues to diffuse across regions, AI integration has been observed in less-developed regions, particularly those geographically adjacent to the developed regions. This implies that these less-developed regions can access extra-regional AI capabilities to compensate for their limited local AI resources. This is consistent with previous research showing that peripheral regions can access key enabling technologies from nearby developed regions to drive innovation (Montresor & Quatraro, 2017). Based on this discussion, we hypothesize the following:

Hypothesis 3: Extra-regional AI relatedness moderates the lack of intra-regional AI relatedness, thereby facilitating the integration of AI into regional technological domains.

Data and methodology

Data

China and the U.S. are selected as the focal area for this research for two main reasons. First, China and the U.S. are key global players in the field of AI. The 2024 Artificial Intelligence

Index, published by the Stanford Institute for Human-Centered Artificial Intelligence (Stanford HAI) shows that China dominates in AI patents worldwide. In 2022, China accounted for 35.31% of global AI patents and the U.S. accounted for 12.08% of global AI patents, outpacing the EU (1.17%). Beyond patents, China and the U.S. also play key roles in developing machine learning models. In 2023, 15 notable AI models were created by China-based institutions, second only to 61 developed in the U.S. (Stanford HAI, 2024). Second, China and the U.S. are at the forefront of AI integration compared to other advanced countries. According to the IBM Global AI Adoption Index (2023), 50% of businesses in China have integrated AI into their processes, and 35% integration rate among companies in the U.S. These factors position China and the U.S. as prime candidates for studying the integration of AI in regional technological domains, offering methodological advantages for this article's quantitative research design.

We use domestic invention patents from the China National Intellectual Property Administration (CNIPA) database the United States Patent and Trademark Office (USPTO) database to identify AI technology and calculate relevant indicators. The CNIPA and USPTO database include all patent registered in China and the U.S., containing information such as patent title, abstract, application date, applicants' names and addresses, and International Patent Classification (IPC) codes. We use the application year to mark the date of invention, as it is closer to the data of the development of the invention. The patents examined are all granted and are regionalized at the city level based on the inventor's address in China and at the Metropolitan statistical areas (MSA) level based on the inventor's address in the U.S.

Based on the CNIPA and USPTO database, we construct our dataset in three steps. First the analysis covers the period from 2001 to 2020, as approximately 99% of AI-related patents in China have been observed since the 2000s. As a result, the analysis in the U.S. alco covers the period from 2001 to 2020. Second, to reduce the sensitivity of AI integration rate and mitigate the effects of sporadic changes in the number of AI-related patents, we cut the left tails of the distributions and restrict our analysis to cities with at least 10 AI-related patents during the period of 2001-2020[2], following the approach of Hidalgo (2021). Third, although AI can be integrated into both AI and non-AI technological domains, our primary focus is the integration of AI into non-AI technological domain. Consequently, we limit our analysis to the non-AI technological domains that have integrated AI[3], based on the four-digit of IPC classification codes. Additionally, data from individual city statistical yearbooks are incorporated to supplement the dataset.

Dependent variables

Our dependent variable is $\text{AI\_Integration\_Rate}_{r,i,t}$, which measures the integration rate of AI technology within a specific technological domain *i* in region *r* in time *t*. Constructing this variable involves three key steps. The first is identifying AI technology. We adhere to the PATENTSCOPE Artificial Intelligence Index published by WIPO, a criterion widely used in economic geography studies, such as Buarque et al. (2020) and Xiao & Boschma (2023). This index provides IPC codes that enable searches for AI techniques (e.g., machine learning, probabilistic reasoning) and AI functional applications (e.g., computer vision, natural language processing). The second is counting co-occurrences. We count the number of each technological domain that co-occurs with AI technology within the same patent document. The logic here is that if a technological domain integrates with AI, they will both be mentioned in the same patent document (Petralia, 2020; Kemeny et al., 2022). For example, if wind power generation technology integrates AI to collect real-time performance data and optimize operations (Lee & He, 2021), both AI technology and wind power technology will be claimed in the patent document. The third is calculating the integration rate of AI technology in a specific technological domain in regions. This rate is the share of co-occurrences with AI technology out of the total number of patents in that technological domain. For example, if a technological domain *i* appears in 10 patent documents, with 5 of those documents also including AI technology, the integration rate of AI in that technological domain *i* would be 50%

[2] Robustness checks are implemented for different thresholds, namely lower (e.g. 0, 5) or higher (e.g. 20). The results are robust to these tests.
[3] We also run the regression for all technology domains that includes both ai and non-ai technology domains. The results remain unchanged.

(5/10).

Independent variables

The first independent variable is intra-regional AI relatedness density $Intra\_AI\_RD_{r,i,t}$, which measures how close or distant a given technology i is to the local stock of AI technology within region r in time t. This variable is calculated in three steps.

The first step is to calculate the technological relatedness between two individual technologies using the co-occurrence method (Feldman et al., 2015). The underlying logic is that two technologies (four-digit IPC codes) are considered related if they are repeatedly mentioned together in the same patent document. To quantify this relationship, we calculate the number of times any two technologies appear together in a patent, and then standardize it count using the method presented by Feldman et al. (2015). In doing so, we calculate the relatedness between technologies i and j ($\mathrm{S}_{i,j}$) as:

$$\mathrm{S}_{ij} = \frac{N_{ij}}{\sqrt{N_i * N_j}}$$

where N_{ij} denotes the number of patents that lists technologies i and j together, N_i and N_j are the total number of patents listing technologies i and j, respectively. The elements on the principal diagonal of the relatedness matrix S are set to 1, indicating that a technology is fully related to itself.

The second step calculate the relatedness density of a given technology i to the existing knowledge based in region r in year t, we follow the method by Hidalgo et al. (2018) and calculate as follows:

$$Relatedness\ Density_{r,i,t} = \frac{\sum_{j \neq i} \mathrm{S}_{ijt} * \mathrm{RTA}_{rjt}}{\sum_{j \neq i} \mathrm{S}_{ijt}}$$

where S_{ijt} is the relatedness between technologies i and j in year t, and RTA_{rjt} is a binary variable that assumes the value 1 when a region r has a greater share of patents in technology j in year t than the reference region (i.e., China as a whole); and 0 otherwise. The specific formula is as follows.

$$RTA_{r,i}^{t} = 1, if \ \frac{patents_{r,i}^{t} / \sum_i patents_{r,i}^{t}}{\sum_r patents_{r,i}^{t} / \sum_r \sum_i patents_{r,i}^{t}} > 1 \ and \ 0 \ otherwise.$$

where $patents_{r,i}^{t}$ represents the total number of patents in technology *i* in region *r* in year *t*.

The third step is to break down the relatedness density into AI and non-AI relatedness density, which measures the relatedness density of a given technology *i* to the local stock of AI and non-AI technologies. The specific formula is as follows.

$$Intra\_AI\_RD_{r,i,t} = \frac{\sum_{j \neq i} (\mathrm{S}_{ijt} * \mathrm{RTA}_{rjt}) * \mathrm{AI}_j}{\sum_{j \neq i} \mathrm{S}_{ijt}}$$

where AI_j = 1 if j ∈ AI technology, and 0 otherwise.

$$Intra\_NO\_AI\_RD_{r,i,t} = \frac{\sum_{j \neq i} (\mathrm{S}_{ijt} * \mathrm{RTA}_{rjt}) * \mathrm{NO\_AI}_j}{\sum_{j \neq i} \mathrm{S}_{ijt}}$$

The second independent variable, extra-regional AI relatedness density $Extra\_AI\_RD_{r,i,t}$, measures for each technology *i* the extent to which a region *r* is linked with other regions *s* that are specialized in AI technologies *j* to which technology *i* is related, but that are missing in region *r* (i.e., in which region *r* is not specialized). This calculation follows the method by Balland & Boschma (2021) and involves six steps. The first step is to calculate AI_RD for technology *i* in all regions *s*, as explained above. The second step is to determine for region *r* which technologies *j* are missing in region *r* (RTA < 1) to which technology *i* is related. The third step is to determine which regions are specialized in these technologies *j* (RTA > 1) related to technology *i* that are missing in region *r*. The fourth step is to sum all AI_RD around technology *i* for all regions *s* that have a specialization in technologies *j* (RTA > 1) in which region *r* is not specialized. This sum of all AI_RD around technology *i* for all regions *s* is called AI_RD_Added ($AI\_RD\_\mathrm{Added}_{r,s,i,t}$), which measures the amount of AI_RD that can potentially be added by other regions to the AI_RD of region *r* in that technology *i* because these regions are specialized in AI technologies *j* related to technology *i* that are missing in region *r*. The fifth step is to determine the number of inter-regional linkages a region *r* has with each region s ($NL_{r,s,t}$) and multiply it with the AI_RD added of each region s ($AI\_RD\_\text{Added}_{r,s,i,t}$). The sixth step is to sum the scores in the fifth step for all regions s. The specific formula is as follows.

$$Extra\_AI\_RD_{r,i,t} = \sum_{s} (NL_{r,s,t} * AI\_RD\_\text{Added}_{r,s,i,t})$$

$$Extra\_NO\_AI\_RD_{r,i,t} = \sum_{s} (NL_{r,s,t} * NO\_AI\_RD\_\text{Added}_{r,s,i,t})$$

Control variables

$X_{r,i,t-1}$ is a vector of control variables at both regional and region-technology level. The regional-level control variables include population (Pop), gross domestic product (GDP), research and development (R&D), related variety (RV), number of patents in regions (Tech_Stock), and local government support for digital transformation (Local_Gov_Support). The region-technology-level control variables is the share of each technological domain in regions (Share_Tech).

First, population serves as a proxy for the sizes of the regions. Larger cities are expected to have higher rates of AI integration due to the presence of highly skilled individuals and advanced knowledge infrastructure. Second, GDP is included to account for the level of economic development in a region. We expect that regions with higher GDP are more likely to integrate AI technologies. Third, we control for the regional stock of human capital represented by R&D, and expect a positive relationship between R&D and the AI integration. Forth, RV is used to measure both relatedness and variety across technological activities in a region. Following Frenken et al. (2007), RV is calculated using the entropy method, taking the difference between total entropy at the level of three-digit patent classes and two-digit subcategories. A higher RV indicates that the regional technological stock is more related, which likely increases the probability of learning from and absorbing AI, leading to a positive relationship with AI integration. Fifth, the number of total patents in regions is to proxy for the overall regional innovation capacity. A positive relationship is expected. Sixth, we include the share of patent in each technological domain in regions, which proxies for the inventive capability of each technological domains within a region. We expect a positive relationship, as the ability to access and absorb AI technology requires a certain level of inventive capability within the existing technological domain. Seventh, given the significant role of government in regulating industrial activities in China, we include the degrees of local government support for digital transformation. Following Loughran & McDonald (2011), we use the word count method in text analysis to construct the indicator (see Appendix 1). A positive relationship between government support and AI integration is expected.

Empirical Strategy

To answer the research questions, the following econometric model is proposed:

$$\text{AI\_Integration\_Rate}_{r,i,t} = \beta_0 + \beta_1 Intra\_AI\_RD_{r,i,t-1} + \beta_2 Extra\_AI\_RD_{r,i,t-1} + \beta_3 X_{r,i,t-1} + \gamma_r + \gamma_i + \gamma_t + \varepsilon_{r,i,c}$$

where β_0 represents the constant term, and $\varepsilon_{r,i,c}$ is the regression residual. All the estimations include region, technology, and time fixed effects (γ_r is a region fixed effect, γ_i is a technology fixed effect, and γ_t is a time fixed effect, respectively), to control for unobserved heterogeneity at these three dimensions. To dampen potential endogeneity issues, all independent variables are lagged by one period, denoted by t-1. In line with Montresor & Quatraro (2017) and Balland & Boschma (2021), time windows of five years are created to smooth the yearly lumpiness of patent data, covering the periods 2001-2005, 2006-2010, 2011-2015, and 2016-2020. All the independent variables are computed for these non-overlapping five-year time windows (except five-year averages of population, GPD and R&D). Finally, all independent variables are z-standardized to facilitate comparison of coefficients. Given the high number of fixed effects included in the estimations, we run a fixed effects linear model with heteroskedasticity-robust standard errors and clustered at the regional level, following Balland et al. (2018).

Results

Descriptive analysis

Figure 2 illustrates the geographical distribution of AI integration rates across Chinese cities from 2001 to 2020. This period is divided into four sub-periods, aligned with significant historical events and the common five-year time windows used in Evolutionary Economic Geography studies: 2001-2005, 2006-2010, 2011-2015, and 2016-2020. The figure examines the space and temporal trends in AI integration across China. During the initial period from 2001 to 2005, AI integration was primarily concentrated in a few provincial capital cities such as Beijing, Shanghai, Hangzhou, Nanjing, and Changchun. These cities had competitive advantages in information technology and manufacturing, positioning them as early adopters of AI. In 2006, Chinese State Council published the National Medium and Long-Term Plan for the Development of Science and Technology (2006–2020), making the first national policy to prioritize AI development by 2020. Following this policy, AI integration began to accelerate and spread beyond the initial provincial capitals. By 2015, AI integration reached a broader range of cities across China. The most recent period from 2016 and 2020 saw a rapid increase in AI integration across China. This acceleration can be attributed to key policy initiatives such as the Internet Plus action plan unveiled by the State Council in July 2015, which aims to integrate the Internet (including AI) with traditional industries to stimulate economic growth. Additionally, the thirteenth five-year plan published in 2016 set ambitious goals for China to become a global leader in AI by 2030. In response to these national priorities, several coastal provinces, including Guangdong, Zhejiang and Jiangsu, launched their own AI development plans. However, this rapid growth also exacerbated regional disparities, with higher AI integration rates in the eastern coastal regions, while the western inland regions lagged behind.

Similarly, Figure 3 illustrates the geographical distribution of AI integration rates across U.S. MSAs from 2001 to 2020. It shows that the West Coast and Northeastern regions have higher AI integration rates, especially in San Francisco-Oakland-Berkeley, San Jose-Sunnyvale-Santa Clara, Boston-Cambridge-Newton, Los Angeles-Long Beach-Anaheim, and New York-Newark-Jersey City. In summary, similar to China, the geographical distribution of AI integration rates across U.S. MSAs shows disparities.

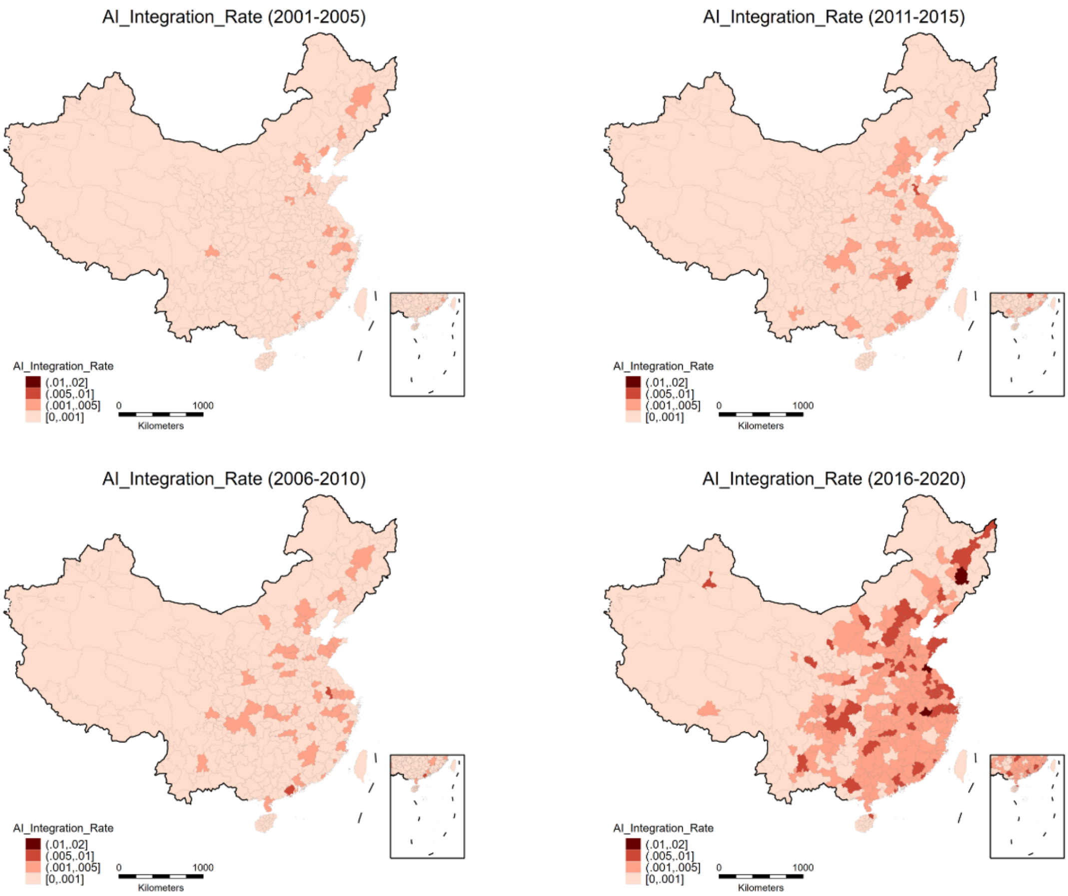

Figure 2. The geography of AI integration across Chinese cities during 2001–2020.

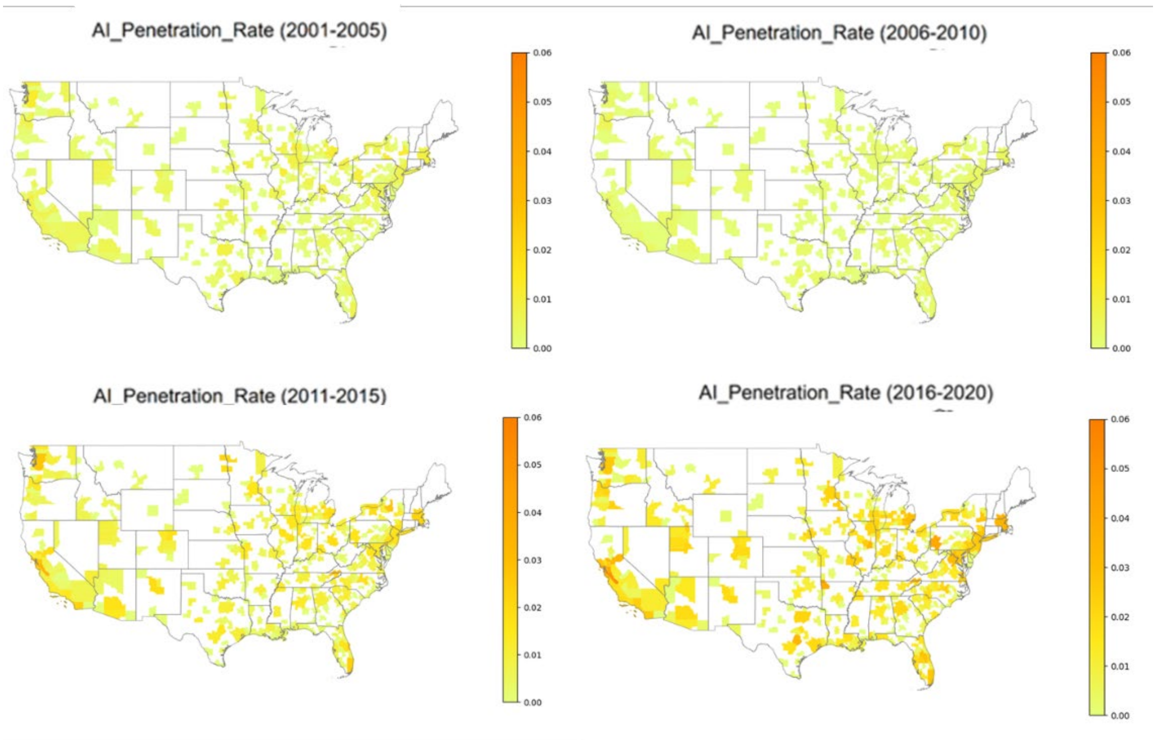

Figure 3. The geography of AI integration across the U.S. MSAs during 2001–2020.

Table 1 presents the integration of AI across various technological domains. It reveals two key trends that are similar in both China and the U.S. First, physics and electricity domains (in terms of IPC Sections G and H) exhibit the highest levels of AI integration. Conversely, domains such as metallurgy, and textiles (in terms of IPC Sections C and D) shows the least integration of AI technologies. Second, AI integration has grown significantly across all technological domains. Take China as an example, AI integration rate in the physics domain (IPC Section G) increased from approximately 0.09% in 2001-2005 to around 1.85% in 2016-2020. Similarly, the electricity domain (IPC Section H) saw an increase from 0.06% to 0.56% over the same periods.

Figure 2 also reveals two differences between China and the U.S. First, the integration rate of AI across all technological domains in the U.S. is higher than that in China. Second, the physics and electricity domains (in terms of IPC Sections G and H) have similar AI integration rates in the U.S., while the AI integration rate in the electricity domain is higher than that in the physics domain in China.

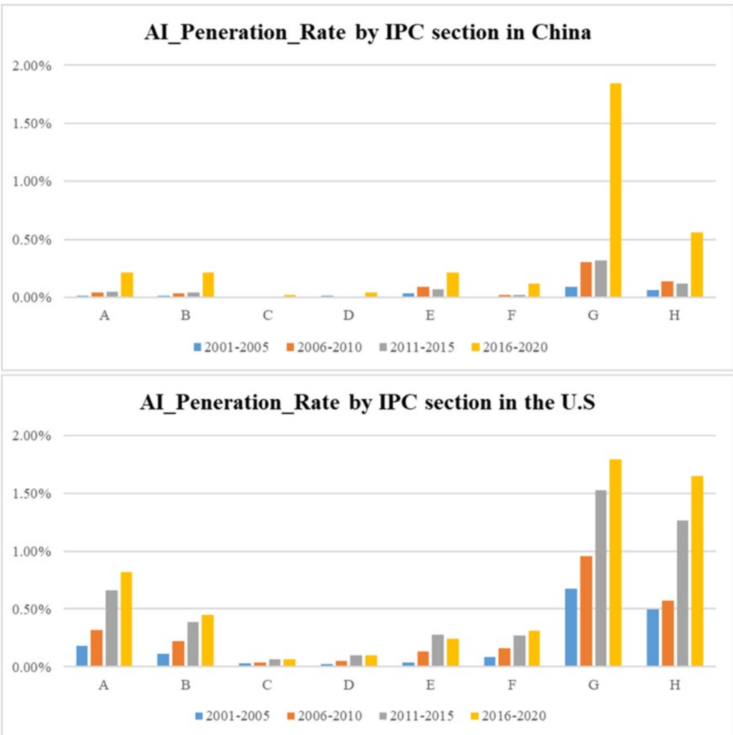

Figure 4. AI integration rate by technological domains in China and the U.S. during 2001-2020.

Note: A: Human Necessities; B: Performing Operations, Transporting; C: Chemistry, Metallurgy; D: Textiles, Paper; E: Fixed Constructions; F: Mechanical Engineering, Lighting, Heating, Weapons; G: Physics; H: Electricity

Figure 3 delves deeper into AI integration at the IPC class level (two-digit level), focusing on the top 5 technology domains with the highest AI integration rate. We find that most of the top 5 technology domains with the highest AI integration rate are similar, that is, G07 (Checking-devices), G08 (Signaling), G06 (Computing, calculating, and counting), and H04 (Electrical communication technology).

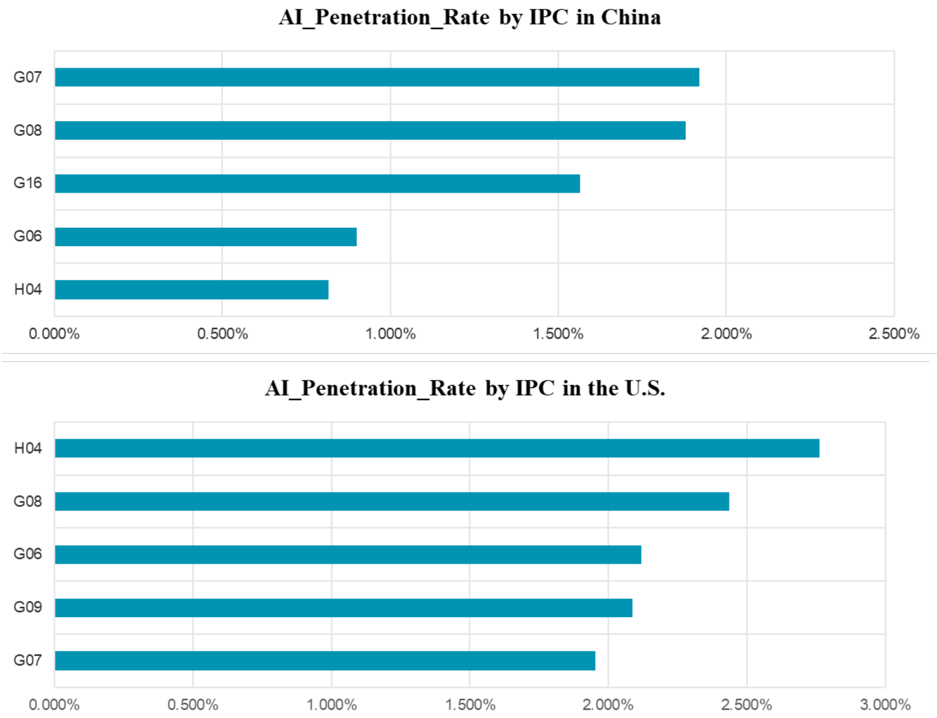

Figure 5. The top 5 technological domain with highest AI integration rate in China and the U.S. during 2001-2020.

Note: G07: Checking-devices; G08: Signaling; G16: Information and communication technology; G06: Computing, calculating, and counting; H04: Electrical communication technology; G06: Computing, calculating, and counting; G09: Education; Cryptozoology; Display; Advertising; Seals;

Regression analysis

Table 1 presents the results for the integration of AI into regional technological domains in China. Column 1 presents the baseline model without the focal variables, which are introduced in a cascade way in column 2 (Intra-regional AI relatedness density), column 3 (Extra-regional

AI relatedness density), column 4 (Intra- and extra-regional AI relatedness density), and column 5 (the interaction term).

First, models 2, 4 and 5 in Table 1 reveal that intra-regional AI relatedness density is positively associated with the integration of AI into regional technological domains (Confirming hypothesis 1). The coefficient reveals that a one-unit increase in intra-regional AI relatedness density leads to an expected increase of approximately 0.098 units in the AI integration rate, assuming other variables remain constant (see model 5), while all the other variables are held constant.

Second, models 3, 4 and 5 in Table 1 reveal that extra-regional AI relatedness density has a positive impact on the integration of AI into a given regional technological domain (Confirming hypothesis 2). Specifically, the positive coefficient reveals that if extra-regional AI relatedness density was to increase by one unit, the expected difference in the AI integration rate would increase by around 0.817 unit (see model 5), holding other variables constant.

Third, model 5 in Table 1 adds an interaction term between intra-regional and extra-regional AI relatedness to assess whether they moderate each other. Our results show that the interaction effect is negative and significant. This finding suggests that extra-regional AI relatedness density can negatively moderate the role of intra-regional AI relatedness (Confirming hypothesis 3). In other words, this implies that regions with weaker capabilities, as indicated by lower intra-regional AI relatedness density, could still enhance AI integration if they can access strong extra-regional AI relatedness density.

Regarding the control variables, the coefficients of GDP and Tech_Stock are significantly negative in some models. These results are in line with the findings of Boschma et al. (2023). This suggests that it is not the size or innovative capacity of regions *per se* that drive AI integration, but rather the extent of their AI relatedness. Similarly, RV plays a negative role in some models, implying that regions with a few specialized and related technological domains are more capable of learning and absorbing AI knowledge. On the other hand, the coefficients of R&D, Tech_Share, and Local_Gov_Sup are positive in some models, which are consistent with our expectations. Finally, the role of Pop is found to be insignificant.

Table 2 presents the results for the integration of AI into regional technological domains in the U.S. The results confirm all our hypotheses. Due to the limited space of the article, we do not provide a detailed analysis.

Table 1: AI Integration Rate in China - Fixed Effects Linear Model

	Dependent Variable (AI Integration Rate)				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
L.Intra_AI_RD		0.137^{***}		0.094^{***}	0.098^{***}
		(0.014)		(0.016)	(0.015)
L.Extra_AI_RD			0.576^{***}	0.479^{**}	0.817^{***}
			(0.206)	(0.199)	(0.301)
L.Intra*Extra_AI_RD					-0.024^{**}
					(0.010)
L.Pop	-0.420	-0.289	-0.395	-0.332	-0.343
	(0.353)	(0.369)	(0.380)	(0.374)	(0.377)
L.GDP	-0.004^{***}	-0.005^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L.Tech_Stock	0.000	-0.000	-0.002^{***}	-0.002^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
L.R&D	0.035	0.053	0.256^{*}	0.213	0.237
	(0.107)	(0.118)	(0.155)	(0.150)	(0.165)
L.RV	-0.058^{*}	-0.055	-0.051	-0.053	-0.050
	(0.034)	(0.037)	(0.036)	(0.036)	(0.037)
L.Tech_Share	0.555^{***}	0.182	0.263	0.157	0.160
	(0.166)	(0.154)	(0.166)	(0.165)	(0.172)
L.Local_Gov_Sup	0.003^{*}	0.003	0.004^{*}	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cons	0.502^{***}	0.448^{**}	0.537^{***}	0.506^{***}	0.531^{***}
	(0.174)	(0.186)	(0.190)	(0.188)	(0.190)
Technology FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	399324	381491	381491	381491	381491
R^2	0.016	0.020	0.021	0.022	0.023

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses

Table 2: AI Integration Rate in the U.S. - Fixed Effects Linear Model

	Dependent Variable (AI Integration Rate)				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
L.Intra_AI_RD		0.368^{***}		0.316^{***}	0.331^{***}
		(0.027)		(0.031)	(0.030)
L.Extra_AI_RD			0.850^{***}	0.597^{**}	0.743^{**}
			(0.320)	(0.264)	(0.336)
L.Intra*Extra_AI_RD					-0.025^{*}
					(0.013)
L.Pop	-0.000	-0.000	-0.000	-0.000	-0.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Tech_Stock	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.RV	0.165	0.246	0.156	0.229	0.232
	(0.177)	(0.195)	(0.177)	(0.192)	(0.193)
L.Tech_Share	13.494***	8.153***	11.822***	7.672***	7.465***
	(1.612)	(1.440)	(1.588)	(1.424)	(1.427)
Cons	-0.124	-0.229	0.099	-0.056	-0.027
	(0.392)	(0.420)	(0.391)	(0.418)	(0.421)
Technology FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	290184	277528	290184	277528	277528
R^2	0.017	0.024	0.021	0.025	0.026

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses

Robustness check

To check the robustness of our findings, we run a complementary analysis. Specifically, we test the role of intra- and extra-regional AI relatedness density by comparing them with the intra- and extra-regional non-AI relatedness density. The results in Table 3 and 4 confirm the robustness of the positive role of intra- and extra-regional AI relatedness density. Interestingly, we found that the roles of intra- and extra-regional non-AI relatedness density are either insignificant or negative, which, to some extent, provides counter-evidence supporting the significant role of AI-specific relatedness.

Table 3: AI Integration Rate in China - Fixed Effects Linear Model (Including Intra- and Extra-Regional Non-AI Relatedness Density Variables)

	Dependent Variable (AI Integration Rate)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
L.In_AI_RD	0.137***			
	(0.014)			
L.In_NO_AI_RD		-0.042***		
		(0.005)		
L.Ex_AI_RD			0.576***	
			(0.206)	
L.Ex_NO_AI_RD				-0.040
				(0.026)
L.Pop	-0.289	-0.398	-0.395	-0.373
	(0.369)	(0.372)	(0.380)	(0.373)
L.GDP	-0.005***	-0.005***	-0.006***	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
L.Tech_Stock	-0.000	-0.000	-0.002***	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
L.R&D	0.053	0.073	0.256*	-0.011

	(0.118)	(0.119)	(0.155)	(0.115)
L.RV	-0.055	-0.013	-0.051	-0.051
	(0.037)	(0.036)	(0.036)	(0.035)
L.Tech_Share	0.182	1.164***	0.263	0.362**
	(0.154)	(0.163)	(0.166)	(0.164)
L.Local_Gov_Sup	0.003	0.003	0.004*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Cons	0.448**	0.421**	0.537***	0.466**
	(0.186)	(0.186)	(0.190)	(0.186)
Technology FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	381491	381491	381491	381491
R^2	0.020	0.018	0.021	0.017

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 4: AI Integration Rate in the U.S. - Fixed Effects Linear Model (Including Intra- and Extra-Regional Non-AI Relatedness Density Variables)

	Dependent Variable (AI Integration Rate)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
L.In_AI_RD	0.368***			
	(0.027)			
L.In_NO_AI_RD		-0.004		
		(0.013)		
L.Ex_AI_RD			0.850***	
			(0.320)	
L.Ex_NO_AI_RD				-0.370***
				(0.083)
L.Pop	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
L.Tech_Stock	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
L.RV	0.246	0.171	0.156	0.169
	(0.195)	(0.183)	(0.177)	(0.178)
L.Tech_Share	0.082***	0.127***	0.118***	0.137***
	(0.014)	(0.016)	(0.016)	(0.016)
Cons	-0.229	-0.118	0.099	-0.303
	(0.420)	(0.404)	(0.391)	(0.404)
Technology FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	277528	277528	290184	290184
R^2	0.024	0.017	0.021	0.017

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Conclusions

In this paper, we examine the influence of intra- and extra-regional AI relatedness, as well as their interaction, on the integration of AI into regional technological domains. Using empirical data from China and the U.S., we uncover significant heterogeneity in AI integration across both regions and technology domains. Regionally, AI integration is highly spatially concentrated in the eastern part of China and the West Coast and Northeastern regions in the U.S. Technologically, the integration of AI is most prevalent in the physics and electricity domains (i.e., IPC Sections G and H). Concerning the impact factors, our econometric results show that intra-regional AI relatedness plays a significantly positive role in the integration of AI into regional technology domains (Confirming hypothesis 1). Second, access to extra-regional AI relatedness also positively affects the integration of AI into regional technology domains (Confirming hypothesis 2). Finally, extra-regional AI relatedness can moderate the lack of intra-regional AI relatedness (Confirming hypothesis 3).

Our contribution is twofold. First, we explore the integration of AI into regional technological domains. This departs from existing literature that primarily focuses on the geography of AI *per se*, e.g., the emergence of the AI in regions (Xiao & Boschma, 2023), the role of AI in regional innovation (Cicerone et al., 2023), and the uneven development of AI technology in regions (Bachtrögler-Unger et al., 2023). Although Buarque et al. (2020) initially explored AI integration, their study was limited to the regional level. In contrast, this article offers a more granular analysis at the regional technological domain level. Second, we construct a framework specifically designed to address the geography of AI integration. While previous concepts like relatedness (Boschma, 2017; Hidalgo et al., 2018) and complementary inter-regional linkage (Balland & Boschma, 2021) provide valuable insights, they do not fully capture the unique characteristic of AI integration. AI integration requires the capability to absorb AI technologies, rather than to absorb non-AI technology. Thus, we introduce the new concept of AI relatedness, which focuses exclusively on AI-related capabilities and excludes non-AI related capabilities, and extends it to both intra- and extra-regional levels.

Our findings offer several important policy implications. First, according to Hypotheses 1 and 2, when aiming to boost AI integration in specific regional technological domain, policymakers should prioritize domains where regions either have intra-regional AI relatedness or can access extra-regional AI relatedness, otherwise policymakers should think twice. Second, according to Hypothesis 3, place-based policies are essential due to the moderate role between intra- and extra-regional AI relatedness. In knowledge-intensive regions, policymakers should pay more attention to intra-regional AI relatedness, whereas policymakers in lagging-behind regions should look more extra-regional to compensate their relatively weak intra-regional capabilities. Third, policymakers should promote the diffusion of AI knowledge from knowledge-intensive regions to lagging-behind regions. This can be achieved through fostering inter-regional cooperation (i.e., the purchase of knowledge embodied in patents, R&D collaboration, attending conferences and trade fairs, informal linkages between friends or former colleagues) and the arrival of new actors (e.g., mobility of highly skilled people, new establishment of extra-regional enterprises) (Trippl et al., 2018).

This paper highlights several avenues for future research. First, the study uses co-occurrence to identify the integration of AI into regional technological domains, based on the presence of AI technology alongside other domain technologies in patent documents. With advancements in natural language processing (NLP), future research could leverage text analysis methods, such as keyword searches (e.g., Petralia, 2020), and large language models like Bidirectional Encoder Representations from Transformers (BERT) (e.g., Dahlke et al., 2024), to enhance the identification of AI integration. Second, extra-regional linkages can manifest in various forms, including the migration and mobility of highly skilled people (Morrison, 2023), global R&D network (Fusillo et al., 2023), and within-firm collaborations across region (Kogler et al., 2023). It would be interesting to investigate the role of different types of extra-regional linkages in AI integration. Third, the current measure of extra-regional AI relatedness density focuses on geographical and cognitive proximity. Future research could expand this by exploring other forms of proximity, such as institutional, social, and organizational proximity (Boschma, 2005), to understand their effects on interregional linkages and AI integration.

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Appendix A

In line with the highly cited paper in Chinese literature (Wu et al., 2021), we develop a dictionary for digital transformation:

- artificial intelligence, business intelligence, image understanding, investment decision assistance system, intelligent data analysis, intelligent robot, machine learning, deep learning, semantic search biometric technology, face recognition, voice recognition, authentication, autonomous driving, natural language processing, big data, data mining, text mining, data visualization, heterogeneous data, credit investigation, enhancement reality, mixed reality, virtual reality, cloud computing, stream computing, graph computing, memory computing, multi-party security computing, brain-inspired computing, green computing, cognitive computing, fusion architecture, billion-level concurrency, exabyte-level storage, internet of things, cyber-physical system, blockchain, digital currency, distributed computing, differential privacy technology, smart finance contract, mobile internet, industrial internet, mobile internet, internet medical, e-commerce, mobile payment, third-party payment, NFC, payment, smart energy, B2B, B2C, C2B, C2C, O2O, network link, smart wearable, smart agriculture, smart transportation, smart medical, smart customer service, smart home, smart investment consulting, smart cultural tourism, smart environmental protection, smart grid, smart marketing, digital marketing, unmanned retail, internet finance, digital finance, fintech, quantitative finance, open banking

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