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The impact of artificial intelligence industry agglomeration on economic complexity

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ABSTRACT

Artificial intelligence (AI) is a fundamental driver of technological and economic growth. However, few studies have focused on the impact of AI industry agglomeration on economic complexity. This study uses a unique dataset of 2,503,795 AI enterprises in China collected through web crawlers to measure AI industrial agglomeration and examine the relationship between AI industry agglomeration and economic complexity in 194 Chinese cities based on Marshall industry agglomeration theory. The study's results show that AI industry clustering increases economic complexity. The mechanism analysis indicates that people and knowledge are the channels through which it boosts economic complexity. Unexpectedly, AI industry agglomeration does not improve the economic complexity index (ECI) through the goods path. This study proposes three possible explanations for this result. First, AI industrial clustering may lead to excessive rivalry in China's intermediate product market. Hence, sharing intermediate inputs has no increasing returns effect. Second, the city's high-end talent is not fairly distributed due to China's uneven development. Finally, policies drive the formation of China's AI industrial agglomeration, which does not develop naturally. Consequently, China should implement a talent- and knowledge-driven AI agglomeration. To avoid overcrowding, policies must match regional development.

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Artificial intelligence; industry agglomeration; economic complexity; agglomeration externality

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1. Introduction

Artificial intelligence (AI) has remodelled various economic activities, such as production (Martínez et al., 2022), distribution (Furman & Seamans, 2019), exchange (Graetz & Michaels, 2018), and consumption (Graetz & Michaels, 2018), profoundly affecting business and production. Industrial robots and AI technologies significantly affect enterprises' production and marketing processes through labour substitution

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(Acemoglu & Restrepo, 2019) and technology updates (Jarrahi, 2018). Many scholars have found that the development of AI improves companies' management, cost benefits, and production efficiency (Matyushok et al., 2021; Wilson & Daugherty, 2018). However, few scholars have focused on the effect of AI on the product complexity index (PCI) or economic complexity index (ECI). The nature and measurements of economic complexity and product complexity are similar; hence, the ECI may be considered an overall measurement of the PCI of a city, region, or country (Mealy et al., 2019).

Product complexity increases by breaking through existing technologies and introducing new products (Hidalgo, 2021). Some scholars have suggested that the determinants of product complexity differ between developed and developing countries (Hidalgo, 2021; Mealy et al., 2019). The higher product sophistication of exports in developed countries is mainly due to higher income levels and economic growth (Mealy et al., 2019), higher technical levels (Hidalgo, 2021), lower trade costs (Nguyen et al., 2020), and the growth of research and development (R&D) investment (Hidalgo, 2021). Developing countries exhibit lower product complexity but are typically affected by the technology spillover of foreign direct investment (FDI) (Antonietti & Franco, 2021), tariff reduction, and trade liberalisation (Mealy & Teytelboym, 2020). Empirical studies using cross-country samples have shown that improvements in institutional quality, labour division, R&D investment, and industrial agglomeration increase the complexity of export products (Dai & Jin, 2014).

Many scholars have investigated whether industrial agglomeration may improve product sophistication but have not reached a consensus (Klein & Crafts, 2020; Mo & He, 2013; Pavelkova et al., 2021). Most scholars contend that industrial agglomeration reduces the uncertainty of developing high-tech products by generating positive externalities (Klein & Crafts, 2020) and the cost of breaking through existing technologies (Mo & He, 2013) to improve the technical complexity of products, ultimately increasing the regional ECI. Other studies suggest that economic agglomeration may increase competitiveness among businesses and help them build political links (Pavelkova et al., 2021). This phenomenon may hinder product complexity.

AI industrial agglomeration is defined as the concentration of enterprises using AI technologies and connected companies in a geographical area owing to their commonalities and complementarities. According to Marshall's theory of agglomeration externalities (Marshall, 2009), agglomeration in the AI industry may generate externalities through labour reservoirs (people), intermediate product sharing (goods), and knowledge and technology spillovers (knowledge), reducing production costs and increasing labour productivity. Economies of scale may be achieved by sharing intermediate products and public goods, reducing transportation costs per unit distance, and sharing company information (Deng, 2021; Fan & Scott, 2009; X. Wang et al., 2021). However, as the degree of AI industry agglomeration increases, public resources face increasing pressure (Pavelkova et al., 2021; X. Wang et al., 2021). Companies may abandon key technological advancements favouring simpler ones (Meliciani & Savona, 2015), and over agglomeration of the AI industry has a crowding-out effect (X. Wang et al., 2021). Moreover, research based on micro-geographical perspectives (X. Wang et al., 2021) indicates an unequal agglomeration effect on product innovation.

Most research on high-tech industry agglomeration has focused on industrialised countries (Ellison et al., 2010; Meliciani & Savona, 2015; Pavelkova et al., 2021). Hence, whether the conclusions and policy recommendations from industrialised countries also apply to China is unclear. Therefore, the impact of China's AI industry agglomeration on economic complexity must be further explored. First, due to its low-cost advantages and demographic rewards, China has achieved miraculous economic growth and export development since its reforms and opening up (Krugman, 1994). China's economic growth is constrained by an unequal industrial structure, low export added value, and a lack of neck-locking technology (Liu & Tie, 2020). As the Chinese society and the economy evolve, the role of AI expands (Furman & Seamans, 2019; Martín & Fernández, 2022). China has made AI a national priority, seeking to use AI to improve technology and increase product complexity (Xie et al., 2021). China's population and industrial structure have created enough data and market needs for AI development. In addition, the agglomeration effect is strongly related to geographic distance (Klein & Crafts, 2020; Shao et al., 2018), and China has a large geographical area and considerable regional disparity. Finally, China's industrial agglomeration model is distinct from that of industrialised countries (Shao et al., 2018; X. Wang et al., 2021). Instead of market economies of scale, policies have induced China's industrial agglomeration (X. Wang et al., 2021). Therefore, the clustering effect of China's AI industry is complex.

Can AI industry agglomeration boost product complexity or the ECI? If so, how does the AI industry promote ECI growth? Is there any disparity in the impact of AI industry agglomeration across regions? The solution to these questions is directly related to whether China may upgrade its industry and enhance its development quality, leading to a new wave of competition and advantages.

To explore these issues, we construct a novel dataset of 2,503,795 AI enterprises using web crawler technology to measure industrial agglomeration in China. To the best of our knowledge, this is the first study to assess AI industry agglomeration at the city level. We extend previous studies on the impact of AI on the social economy by examining the relationship between AI industry agglomeration and ECI. Finally, we build on Marshall's theory of agglomeration externalities to explore the inner-impact mechanism in the relationship of interest.

The remainder of this paper is organised as follows. Section 2 reviews the literature. Section 3 formulates the research hypotheses, and Section 4 describes the variables, data sources, and empirical models. Section 5 presents and discusses the empirical results, exploring the impact mechanism of AI industry agglomeration on the ECI. Finally, Section 6 concludes and provides policy implications.

2. Literature review

The impact of AI on social and business economies is crucial. Researchers have examined the effects of AI on economic growth (Furman & Seamans, 2019), employment (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017; Mutascu, 2021), corporate competition (Sun & Hou, 2021), and company managerial efficiency (Di Vaio et al., 2020) at various levels. Some (Acemoglu & Restrepo, 2019; Brynjolfsson et al., 2019) argue that AI-derived technology boosts efficiency but not productivity. According to Bergeaud et al. (2017), from 1890 to 2015, the total factor productivity growth rates of the United States, the Eurozone, the United Kingdom, and Japan have continued to decline, casting doubts on the impact of AI (Frey & Osborne, 2017). Some studies contend that AI increases unemployment and inequality (Acemoglu & Restrepo, 2019). Mutascu (2021) predicts that AI will replace 54% of occupations in Europe in the next 10–20 years. Others propose that AI may supplement existing labour and assets, enhancing labour productivity (Graetz & Michaels, 2018) and capital efficiency (Brynjolfsson et al., 2019). According to Acemoglu and Restrepo (2019), automation replaces and creates new jobs. They contend that the employment creation effect may boost productivity by increasing the demand for labour in non-automated tasks.

At the micro level, AI influences corporate operations and decision-making in numerous industries (Di Vaio et al., 2020; Goldfarb & Trefler, 2019). Sun and Hou (2021) reveal that the development of AI in China boosts the total factor productivity of traditional manufacturing industries such as textiles and apparel. However, AI has no significant effect on disruptive high-end manufacturing industries such as computer communications. Scholars have also investigated AI's impact on company management. For instance, Di Vaio et al. (2020) contend that AI and related technology influence corporate human resource management and reputation risk management. According to new trade theory, AI impacts business export decisions and global trade (Goldfarb & Trefler, 2019). However, few studies have examined whether AI may increase product complexity and, thus, exportability.

The existing PCI/ECI investigations focus on their measurements and determinants. Several authors have proposed ECI metrics. For instance, Hidalgo and Hausmann (2009) have introduced a reflection method to measure economic complexity. However, Tacchella et al. (2012) have pointed out that Hidalgo and Hausmann's (2009) measure ignores the link between competitive advantage and export diversification. They propose a new nonlinear iterative algorithm to define a self-consistent and non-monetary index for product and economic sophistication from a data-driven perspective. Furthermore, some studies contend that economic complexity reflects a country's technological strengths, as regional diversification is linked to technology portfolios (Ivanova et al., 2017). Ivanova et al. (2017) consider countries, product groups, and patents to measure economic complexity. In addition, novel methods based on Hidalgo and Hausmann's (2009) reflection method have been proposed (Hidalgo, 2021; Utkovski et al., 2018). Several researchers have compared existing economic complexity metrics (Albeaik et al., 2017; Hidalgo, 2021). However, the method proposed by Hidalgo and Hausmann (2009) is the most widely used approach for measuring the ECI

Previous studies have focused on the determinants of the ECI from the perspective of factor endowments (Z. Wang & Wei, 2010), FDI (Antonietti & Franco, 2021), the global value chain division of labour (Dai & Jin, 2014), and spatial agglomeration (Balland et al., 2020; Malesky & Mosley, 2018; Storper, 2018). Z. Wang and Wei (2010) argue that human capital and the local government's high-tech zone policy positively affect economic complexity. However, natural resources, foreign investment, and processing trade have a marginal impact on the ECI of Chinese cities. Antonietti and Franco (2021) find that the effect of inward FDI stock per capita on the ECI varies by country. Dai and Jin (2014) show that the institution quality positively affects the technical complexity of exports. Researchers have also addressed the determinants of the ECI based on geographical agglomeration. For example, Malesky and Mosley (2018) claim that industry clustering boosts Chinese firms' PCI. The agglomeration economy is more prominent in industrialised nations than in emerging countries (Thisse, 2018). Balland et al. (2020) find that regional characteristics influence agglomeration effects. They argue that economic agglomeration improves the ECI because complex economic operations require greater in-depth knowledge and labour division. Klein and Crafts (2020) classify industrial clusters as specialised or diversified. Storper (2018) examines the relationship between agglomeration economies and product complexity and finds that agglomeration externalities differ.

The methods for measuring industrial agglomeration include location entropy (Mo & He, 2013), the Herfindahl-Hirschman index (Klein & Crafts, 2020), the space Gini coefficient (X. Wang et al., 2021), the Ellison and Glaeser's (E-G) index (Faggio et al., 2020), and the Duranton and Overman's (DO) index (Duranton & Overman, 2005; Shao et al., 2018). Mo and He (2013) use location entropy to measure the degree of agglomeration of high-tech industries in 25 Chinese provinces based on the industry's output value. Klein and Crafts (2020) employ the Herfindahl-Hirschman index and employment data to observe the dynamic changes in the US manufacturing industry agglomeration from 1880 to 1930. X. Wang et al. (2021) use the space Gini coefficient and employment data to measure the agglomeration degree of modern services in 41 cities in China's Yangtze River Delta city group. Faggio et al. (2020) deploy employment data from 97 three-digit industries in the UK and use the E-G index to measure industry agglomeration. Others use the DO index based on the longitude and latitude of firms to measure industrial agglomeration (Duranton & Overman, 2005; Shao et al., 2018). The DO index is a metric for industrial agglomeration proposed by Duranton and Overman (2005). Researchers have developed various agglomeration metrics depending on the research objectives and data acquired. Using the DO index to measure AI industry agglomeration has numerous benefits. Based on the distance between firms, the DO index may better indicate the agglomeration of businesses (Shao et al., 2018). Unlike other agglomeration measurement approaches, the DO index does not require prior area delimitation (Duranton & Overman, 2005) and may measure the entire continuous space, handling enterprise-scale distributions more flexibly.

Existing research mainly focuses on the impact of AI on economic growth (Furman & Seamans, 2019), employment (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017; Mutascu, 2021), corporate competition (Sun & Hou, 2021), and company managerial efficiency (Di Vaio et al., 2020). Many studies have examined how factor endowments, spatial agglomeration, the global value chain division of labour, and FDI affect product complexity. However, few studies have investigated the association between AI and the ECI. Moreover, AI helps companies become superstars, making it easy for AI companies to cluster. On the one hand, because AI is associated with higher fixed costs and lower marginal costs, companies using AI technology have higher barriers to entry. On the other hand, the platform economy is expected to become a crucial economic model due to the significant impact of AI. The platform economy has cross-edge network externalities and may quickly become an oligopoly (Deng, 2021; Pavelkova et al., 2021). A significant gap is observed in the effect of AI industry agglomeration on the ECI. Hence, the action mechanism in the relationship between AI industry agglomeration and the ECI needs to be further investigated.

3. Theoretical background and hypotheses

3.1. AI industry agglomeration and the ECI

The industrial agglomeration of traditional manufacturing and modern services has been previously investigated (Klein & Crafts, 2020; Mo & He, 2013; Pavelkova et al., 2021; Shao et al., 2018). Previous studies have measured industrial agglomeration based on employment, productivity, and output values. However, as AI is an emerging industry, obtaining relevant data may be challenging. AI has played a vital role in transforming modern society and the economy, generating new waves of digitalisation and intelligence. All countries deploy AI and seek new regional competitive advantages to gain a future first-mover advantage (Furman & Seamans, 2019). Hence, an in-depth analysis of AI industry aggregation in terms of economic complexity is essential.

AI industry agglomeration may increase the ECI in two ways. First, the development of AI may directly improve the ECI. As a critical technological innovation (Acemoglu & Restrepo, 2019), AI may help businesses enhance manufacturing technologies and produce items with higher technical content. These technologies may use network approaches to understand complex systems and improve technical product content by increasing dynamic data gathering and processing capabilities (Hidalgo, 2021). Second, AI may be regarded as a new factor of production (Acemoglu & Restrepo, 2017; Brynjolfsson et al., 2019), which may supplement existing labour and assets (Goldfarb & Trefler, 2019), improve labour productivity (Brynjolfsson et al., 2019) and capital efficiency (Hidalgo, 2021), and help enhance the total factor productivity (Brynjolfsson et al., 2019). Research shows that higher productivity and capital efficiency lead to higher profitability (Sun & Hou, 2021). Therefore, adequate capital use allows companies to tolerate the uncertain costs of technological development and the fixed costs of exporting high-tech and complex products (Goldfarb & Trefler, 2019). This awareness encourages companies to focus on high-tech and complex products. Guan and Cheng (2020) show that companies' total factor productivity directly impacts the complexity of export technology. Hence, AI may positively affect the ECI by increasing total factor productivity. Third, the lower costs of AI-based industrial robots have helped them grow in popularity. The use of AI-related technology may improve labour quality. Industrial robots may replace low-wage workers such as drivers and waiters (Frank et al., 2019). Therefore, an enterprise's low-wage labour demand decreases. However, industrial robots may reintroduce labour into new tasks by changing task content. The creation effect occurs when the popularity of industrial robots creates new jobs in coding, software and app development, and data backup (Graetz & Michaels, 2018). Creating new jobs and occupations benefits the human capital of the job market. These dual effects may enhance labour quality and increase the ECI.

Agglomeration effects may directly promote ECI growth via a secondary influence path. First, by leveraging the scale economy effect, AI firm clustering may help an area or city develop more efficiently (Furman & Seamans, 2019). The concentration of AI enterprises may induce several businesses to invest and relocate (Faggio et al., 2020; Pavelkova et al., 2021). Enterprise clustering may reduce transportation and knowledge acquisition costs (Klein & Crafts, 2020). In addition, the increasing returns to scale may result in a pricing advantage, enhancing the company's ability to compete in product export markets. Second, the AI industry is both knowledge- and capital-intensive and is characterised by constant learning and technological advancement. Knowledge and technology spillover from AI industry agglomeration benefits the entire city (Pavelkova et al., 2021). The AI industry has grown rapidly in recent decades. Several countries, including China, have promoted AI as a national strategy (Xie et al., 2021). Most cities in China prioritise AI (Xie et al., 2021). Social resources outnumber traditional industries, reducing the negative externalities of industrial agglomeration (Acemoglu & Restrepo, 2019; Klein & Crafts, 2020). As AI industry agglomeration grows, the crowding effect is less likely to dominate (McCann & Van Oort, 2019). Hence, we propose the following hypothesis:

H1: AI industry agglomeration has a positive effect on economic complexity.

3.2. The mediating role of per capita human capital in the labour market

Marshall (2009) explains the agglomeration economy using the industrial district theory, acknowledging that externalities cause the geographic agglomeration of enterprises. Marshall defines externalities in three ways. First, industrial agglomeration may create a shared labour market. Second, industrial agglomeration may improve input availability. Third, it may generate knowledge spillover. Hence, industrial agglomeration may generate externalities through people, goods, and knowledge.

A labour market with higher per capita human capital helps form economies of scale (Klein & Crafts, 2020; Pavelkova et al., 2021). Human capital has recently been recognised as an essential factor in enhancing corporate innovation capabilities (Furman & Seamans, 2019; Pavelkova et al., 2021), corporate total factor productivity (Pietrucha & Żelazny, 2020), and company's competitive advantages (Antonietti & Franco, 2021).

In addition, according to product life cycle theory, human capital drives new product introduction and development (Lehmann et al., 2019). Human capital investment helps companies reduce the time of product development and improve the life cycle of earnings (Guan & Cheng, 2020). Increasing per capita human capital in the labour market help companies improve product diversification (Antonietti & Franco, 2021) and core technical strength (Deng, 2021), allowing them to develop new products or improve the technical content of existing ones. Hence, we argue that improving the ECI requires increasing per capita human capital in the labour market.

AI industry agglomeration affects product technology content and the ECI, as discussed in H1. In addition, top talent enhances technology, complex production equipment, and knowledge-sharing opportunities. This strategy works best when higher levels of per capita human capital in the labour market support higher agglomeration levels (Liu & Tie, 2020).

According to Marshall's theory of industrial districts (Marshall, 2009) and Porter's theory of industrial clusters (Porter, 2011), AI industry agglomeration improves the ECI by gathering high-end talent. On the one hand, AI companies use industrial robots or AI-related technology to replace low-end labour and create high-end labour positions (Graetz & Michaels, 2018), increasing the demand for high-end talent. The AI industry is knowledge-intensive and requires highly educated workers (Furman & Seamans, 2019). Therefore, AI firms need more high-end technical talent. The influx of high-end talent boosts the labour market's per capita human capital and enhances enterprise technological innovation capabilities, thus improving the ECI (Hidalgo, 2021).

On the other hand, the AI industry's agglomeration facilitates the development of a labour market that shares different talents. A shared labour market facilitates talent flow within and between industries (Du & Vanino, 2021). It may save companies money on high-end talent searches, better matching between AI companies and qualified job seekers. Finally, AI industry agglomeration may generate incentives to develop more high-tech and complex products, helping increase the ECI. Hence, we propose the following hypothesis:

H2: Per capita human capital in the labour market mediates the effect of AI industry agglomeration on the ECI.

3.3. The mediating role of intermediate input product quality

Changes in intermediate inputs may also affect productivity. First, a higher intermediate input product quality requires more complex production technology (Amiti & Konings, 2007) and updated equipment (Halpern et al., 2015), thus increasing production efficiency. Second, the improvement in input positively affects output (Amiti & Konings, 2007). Hence, the quality of intermediate input products is linked to the complexity of final output goods. Finally, companies tend to improve their management to better utilise high-quality intermediate input products (Meng et al., 2020).

Increased productivity allows a company to focus on high-complexity products. Improving intermediate input product quality may improve production efficiency through technology spillover (Liu & Tie, 2020). As a result, the quality of intermediate input products may boost the ECI.

As discussed in H1, we assume that AI industry agglomeration positively affects product technology content and economic complexity. Improvements in the quality of intermediate input products strengthen the productivity effect of economic space agglomeration (Defever et al., 2020). Hence, industrial agglomeration improves enterprise productivity and increases productivity spillovers from improved intermediate input product quality (Ciccone, 2002; Pavelkova et al., 2021).

Based on the theory of industrial districts (Marshall, 2009), AI industry agglomeration may increase the ECI by sharing intermediate inputs. Marshall (2009) proposes that industrial agglomeration increases access to specialised input services by sharing intermediate inputs. As the AI industry agglomerates, the available intermediate inputs become more professional and the products more technical (Ciccone, 2002; Pavelkova et al., 2021). Hence, we propose the following hypothesis:

> H3: Intermediate input product quality mediates the effect of AI industry agglomeration on the ECI.

3.4. The mediating role of innovation and entrepreneurship quality

Innovation and entrepreneurship generate new knowledge (Di Vaio et al., 2020), expand existing knowledge (Di Vaio et al., 2020; Zhou & Li, 2012), and introduce new business models (Foss & Saebi, 2017). They are common ways to improve company productivity and profits (Bergeaud et al., 2017; Brynjolfsson et al., 2019). The benefits of innovation and entrepreneurship are long-term (Nair, 2020), allowing companies to compete and grow. Developing complex technologies may require years of knowledge accumulation and innovation (Antonietti & Franco, 2021; Mealy et al., 2019). Thus, we propose that the ECI positively relates to innovation and entrepreneurship.

The AI industry may affect innovation and entrepreneurship in several ways. AI aids knowledge discovery and integration (Acemoglu & Restrepo, 2019; Brynjolfsson et al., 2019). Thus, the AI industry exhibits advancements in innovation and entrepreneurship. Industrial agglomeration theory (Deng, 2021; Fan & Scott, 2009; Marshall, 2009) suggests that increasing AI industry agglomeration may improve the quality of innovation and entrepreneurship.

As discussed above, H1 discusses the positive relationship between AI industry agglomeration and the ECI. When high-quality innovation and entrepreneurship are simultaneously backed by high AI company agglomeration (Deng, 2021), this pattern may fully use the agglomeration effect. AI industry agglomeration may improve innovation quality and increase knowledge and technology spillovers. Therefore, we propose the following hypothesis:

> H4: Innovation and entrepreneurship quality mediate the effect of AI industry agglomeration on the ECI.

4. Data and methodology

4.1. Data

4.1.1. Economic complexity of the city

The PCI and ECI may be measured in several ways. Hidalgo and Hausmann (2009) have introduced a reflection method to measure economic complexity based on a country's per capita GDP. This method has been used to develop novel economic and product complexity measures. Most researchers aim to improve measurements through algorithms (Hidalgo, 2021; Tacchella et al., 2012; Utkovski et al., 2018). Tacchella et al. (2012) have proposed a novel nonlinear and iterative measure (FI) for product sophistication and country fitness. Utkovski et al. (2018) have proposed a probabilistic learning framework based on Bayesian nonparametric techniques to measure product and country capabilities. However, with the significant change in the social economy and production mode, some scholars have improved the previous methods by focusing on the nature of the ECI (Ivanova et al., 2017). Ivanova et al. (2017) argue that capabilities may be endogenous to models of economic complexity and construct a framework that includes countries, product groups, and patent classes. Some studies have compared the performance of ECI measurements as more measures have been proposed. Albeaik et al. (2017) have introduced a novel and simple measure (ECI+). They then compare ECI+, the ECI provided by Hidalgo and Hausmann (2009), and the FI proposed by Tacchella et al. (2012) to show that ECI + outperforms the other two methods in estimating knowledge intensity and forecasting future economic growth. However, ECI + has poor explanatory power and strict data requirements (Albeaik et al., 2017). As mentioned above, the method of reflection proposed by Hidalgo and Hausmann (2009) to measure the ECI has been widely used and accepted for several years (Hidalgo, 2021; Vu, 2022) and is equivalent to ECI + and FI algorithmically. Therefore, this study adopts the method proposed by Hidalgo and Hausmann (2009) to measure the PCI.

We use data from the UN Comtrade to calculate the PCI. Then, we calculate the ECI at the city level by weighted summation of the PCI based on the city's export data. The data on the trade export value of each city are obtained from the China Customs Data. We present detailed calculations below. The data cover 194 cities from 2000 to 2016.

We define a binary country-product matrix M with elements M_{cp} to create two measures: ubiquity and diversity. M_{cp} equals one if country c has a revealed comparative advantage (RCA) in producing product p, and zero otherwise. We measure RCA using the Balassa Index (Hidalgo & Hausmann, 2009). When $RCA_{cp} \geq 1$, $M_{cp} = 1$, and $M_{cp} = 0$ otherwise. Hence, we construct a matrix of countries and product M, M_{cp}, as follows:

$$M_{cp} = \begin{cases} 1, & RCA_{cp} \geq 1 \\ 0, & RCA_{cp} < 1. \end{cases} \tag{1}$$

After constructing matrix M, we obtain ubiquity ($k_{p,0}$) by summing the rows of matrix M, representing the number of countries producing a product. We obtain diversity ($k_{c,0}$) by adding up the columns of matrix M, which represents the number of products produced in a country:

$$Ubiquity = k_{p,0} = \sum\nolimits_c M_{cp}, \tag{2}$$

$$Diversity = k_{c,0} = \sum\nolimits_p M_{cp}. \tag{3}$$

Following continuous iterations, we use the expressions *Ubiquity* and *Diversity* to perform mutual corrections to obtain a more refined measure of both attributes.

Equations (4) and (5) are based on the expansion of Equations (2) and (3) and present the average ubiquity and diversity for all countries, respectively:

$$k_{p,N} = \frac{1}{k_{p,0}} \sum\nolimits_c M_{cp} * k_{c,N-1}. \quad (4)$$

$$k_{c,N} = \frac{1}{k_{c,0}} \sum\nolimits_p M_{cp} * k_{p,N-1}. \quad (5)$$

Substituting (4) into (5), we obtain:

$$k_{p,N} = \sum\nolimits_{p'} M_{pp'} k_{p',N-2}, \quad (6)$$

where $M_{pp'} = \sum_c \frac{M_{cp}M_{cp'}}{k_{c,0}k_{p,0}}$, p' represents the products other than p, and N denotes the number of iterations.

In the case of $k_{p,N} = k_{p,N-2} = 1$, $M_{pp'}$ is the eigenvector of Equation (6). However, this eigenvector only comprises values equal to one, which are not informative when used to interpret the intrinsic trade abilities of the country. Therefore, we employ the eigenvector with the second-greatest eigenvalue ($\overrightarrow{Q}$) to capture the largest proportion of the variance.

Hence, we define product complexity for product p as follows:

$$PCI_p = \frac{\overrightarrow{Q_p} - \langle \overrightarrow{Q} \rangle}{stdev(\overrightarrow{Q})}, \quad (7)$$

where $\langle\ \rangle$ refers to the average and *stdev* refers to the standard deviation. Finally, we calculate the ECI at the city level (after the PCI). We use the city's export value of the product as the weight to obtain the ECI of the city, as follows:

$$ECI_{city} = \frac{\sum_p PCI_p * export_{p,city}}{\sum_p export_{p,city}}, \quad (8)$$

where $export_{p,city}$ is the export value of city c for exports of product p.

4.1.2. AI industry agglomeration

This study uses the DO index proposed by Duranton and Overman (2005) to measure AI industry agglomeration in various cities in China. Most studies have calculated industrial agglomeration based on China's industrial enterprise data or economic census data (Mo & He, 2013; X. Wang et al., 2021; Yuan et al., 2020). However, the AI industry is emerging, and data on employment, output value, and productivity are scarce. Therefore, we use the DO index to measure the degree of AI industry agglomeration in Chinese cities based on the longitude and latitude of AI enterprises. In addition, the data conventionally used for analysis may not accurately reflect the agglomeration and distribution of AI companies. Hence, this study uses a novel dataset of 2,503,795 AI enterprises in China and the web crawler technique to overcome the above limitations. We obtain data from a corporate credit information enquiry website in China, which provides information such as company name, exact address, industry type, registration time, and exit time. We limit the business scope of the AI industry based on the Strategic Emerging Industry Classification issued by the National Bureau of Statistics of China in 2018.

The calculation of the DO index includes three steps. The first step estimates the kernel density function. For an AI industry with n establishments, we calculate the Euclidean distances for each pair of establishments. When an AI company is established, $\frac{n(n-1)}{2}$ different bilateral Euclidean distances may be calculated. However, bilateral Euclidean distances are only a rough estimation of the actual physical distance between AI companies due to errors (Duranton & Overman, 2005). To decrease this noise in the computation, we use a kernel-smooth method to estimate the distribution of bilateral Euclidean distances.

Let $d_{i,j}$ be the Euclidean distance between AI company i and j. Assuming n AI enterprises within the AI industry, the estimated value of the bilateral distance density (K-density) at any point d is:

$$\widehat{K_A(d)} = \frac{1}{n(n-1)h}\sum\nolimits_{i=1}^{n-1}\sum\nolimits_{j=i+1}^{n} f\left(\frac{d-d_{ij}}{h}\right), \tag{9}$$

where h refers to bandwidth, and $f(\cdot)$ is the Gaussian kernel function.

Second, we construct counterfactuals. In line with Shao et al. (2018), we assume that the location of all enterprises in China's AI industry constitutes a set of possible locations for any company, and each company may randomly choose its location from this set. In each simulation, we randomly select the same number of locations as the number of enterprises to estimate the bilateral distance between these locations and their K-density function. Following Duranton and Overman (2005) and Shao et al. (2018), we conduct 1000 random simulations.

Third, we calculate the local confidence intervals. Comparing the actual K-density estimate with the K-density estimate of the simulated distribution determines whether an industry is agglomerated. According to Duranton and Overman (2005) and Shao et al. (2018), 40 km is the median distance between all the pairs of AI enterprises. As the local confidence interval only reflects the local information of industry agglomeration and dispersion at a certain distance, it cannot capture global agglomeration and dispersion (Duranton & Overman, 2005; Shao et al., 2018). Therefore, we focus on the global confidence interval, a joint estimation of the local extreme values at multiple distances (Duranton & Overman, 2005). We obtain a 95% global confidence interval by interpolating the local extreme values at multiple distances. Let $\overline{\overline{K_A}}(d)$ be the upper confidence band of the AI industry and K_A (d) be the lower confidence band of the AI industry. The AI industry is considered to have global localisation at a 5% confidence level if $\widehat{K_A}(d) > \overline{\overline{K_A}}(d)$ for at least one $d \in [0, 40]$. Similarly, when $\widehat{K_A}(d) < \overline{\overline{K_A}}(d)$ for at least one $d \in [0, 40]$, the AI industry is not localised, implying a global dispersion. For the AI industry, the global localisation index is defined as:

$$\lceil_A(d) = \max\ \{\widehat{K_A}(d) - \overline{\overline{K_A}}(d),\ 0\}, \tag{10}$$

and the global dispersion index is:

$$\psi_A(d) = \begin{cases} \max\left\{\underline{K_A}(d) - \widehat{K_A}(d),\ 0\right\}, & if \sum_{d=0}^{d=40} \lceil_A(d) = 0 \\ 0, & otherwise. \end{cases} \tag{11}$$

Hence, we may calculate the DO index of AI industry agglomeration. The geographical area of each city in China is different. To obtain the industrial agglomeration index of subsector A in city c, where A is a subsector of the AI industry, such as AI manufacturing, AI information transmission, and the software and information technology service industry, this study uses the agglomeration ratio method (Shao et al., 2018) to eliminate the impact of the difference in the size of the geographical area, as follows:

$$DO_{A,c} = \frac{\sum_d I_d}{d_{max}}, \tag{12}$$

where $I_d = \begin{cases} 1, & if\ \widehat{K_A}(d) > \overline{\overline{K_A}}(d), \\ 0, & else \end{cases}$ and d denotes the greatest distance. $DO_{A,c}$ is defined as the agglomeration index of A subsector in City c.

To compare the agglomeration of AI industries at the city level, we calculate the overall AI industry agglomeration index by weighting the number of enterprises in subsector A of the AI industry in city c, as follows:

$$Do_c = \frac{\sum_A DO_{A,c} \times Count_{A,c}}{\sum_A Count_{A,c}}, \tag{13}$$

where $Count_{A,c}$ is the number of companies in subsector A of the AI industry in city c.

4.1.3. Control variables

We control for four variables that potentially impact the ECI. Table 1 presents their measurements and sources.

The first variable is manufacturing development (*Manu*). The manufacturing industry and export trade are strongly related. Advanced manufacturing directly increases regional product complexity. Following Filatotchev et al. (2011), we calculate *Manu* as the ratio of the number of employees in the manufacturing industry to the number of employees in the region.

The second control variable is financial development (*Fin*). External financing may adjust the industry structure (Nguyen et al., 2020; Pavelkova et al., 2021) and provide financial support for high-tech industries (Nguyen et al., 2020) through resource allocation, increasing the ECI. Following Filatotchev et al. (2011), we calculate *Fin* as the ratio of the number of employees in the financial and insurance industries to the number of employees in the region.

The third variable is FDI (*FDI*). FDI introduces foreign products and technologies into companies, causing technological spillover, and enhancing a company's technological R&D capabilities, thus increasing ECI. Following X. Wang et al. (2021), we

Table 1. Variables and measurements.

Variables	Measurements	Data sources	Sources
Manufacturing Development (*Manu*)	The ratio of the number of employees in the manufacturing industry to the number of employees in the region	China city statistical yearbook	Filatotchev et al. (2011)
Financial Development (*Fin*)	The ratio of the number of employees in the financial and insurance industry to the number of employees in the region	China city statistical yearbook	Filatotchev et al. (2011)
FDI	The regional amount of foreign capital used for the gross regional product	China city statistical yearbook; The People's Bank of China	X. Wang et al. (2021)
Infrastructure (*Infra*)	Per Capita Area of Paved Roads in the city (sq.m.)	China city statistical yearbook	Yuan et al. (2020)
Per capita human capital in the labour market (*Labour*)	The proportion of the number of college students in the labour market	China city statistical yearbook	Filatotchev et al. (2011)
Intermediate Input Product Quality (*Quality*)		China's Industrial Enterprise Database; China Customs Data	
Innovation and Entrepreneurship Quality (*Innovation*)	Innovation and entrepreneurship index	Peking University Open Research Data Platform	

Source: Own processing.

measure *FDI* by the regional amount of foreign capital used in the gross regional product.

The last control variable is infrastructure (*Infra*). Infrastructure positively affects the complexity of high-tech products. An excellent infrastructure may save inventory and production costs and reduce production uncertainty (Yuan et al., 2020). Following Yuan et al. (2020), we use the per capita area of paved roads in the city to measure *Infra*.

4.1.4. Mediators

We introduce three mediating variables. Table 1 summarises their measurements and sources. The first is the labour market's human capital per capita (*Labour*). Following Filatotchev et al. (2011), we measure *Labour* using the proportion of the number of college students in the labour market.

The second is intermediate input product quality (*Quality*). We calculate *Quality* based on Defever et al. (2020). Due to the lack of data in Dazhou, Ordos, Tongliao, and Zhuzhou, and the lack of information regarding product unit prices in 2016 in China Customs Data, we only examine the mediating effect of *Quality* in 190 Chinese cities from 2000 to 2015.

The third mediator is the quality of innovation and entrepreneurship (*Innovation*). We employ China's innovation and entrepreneurship index from the Peking University Open Research Data Platform to measure *Innovation*. The database only covers prefecture-level cities in China. Data for Beijing, Shanghai, Tianjin, and Chongqing are missing; hence, we use data from 190 cities from 2000 to 2016 to analyse the mediating effect of *Innovation*.

4.2. Model specification

To test the H1, this study employs the following panel regression model:

$$ECI_{i,t} = \alpha_0 + \alpha_1 DO_{i,t} + \varphi X_{i,t} + u_i + u_t + \varepsilon_{i,t}, \tag{13}$$

where t denotes the year ($t = 2000, 2001, \ldots\ldots, 2016$), i is the number of cities ($i = 1, 2, \ldots\ldots, 194$), and $ECI_{i,t}$ is the economic complexity of city i in year t, the core dependent variable. Similarly, $DO_{i,t}$ denotes the level of AI industry agglomeration in city i in year t, and it is the core independent variable. α_0 is the intercept term. $X_{i,t}$ represents the set of control variables, α_1 and φ are the estimated coefficients on $DO_{i,t}$ and $X_{i,t}$ respectively, u_i and u_t are a full set of city dummies and time effects capturing the common shocks to the ECI of all cities, and $\varepsilon_{i,t}$ denotes the error term capturing all the other omitted factors.

To evaluate the effect of mediators, following Yuan et al. (2020), we construct a mediating effect model to test H2, H3, and H4, as follows.

$$ECI_{i,t} = \alpha_0 + \alpha_1 DO_{i,t} + \varphi X_{i,t} + u_i + u_t + \varepsilon_{1i,t}, \tag{14}$$

$$M_{i,t} = \beta_0 + \beta_1 DO_{i,t} + \varphi X_{i,t} + \lambda_i + \lambda_t + \varepsilon_{2i,t}, \tag{15}$$

$$ECI_{i,t} = \gamma_0 + \gamma_1 DO_{i,t} + \gamma_2 M_{i,t} + \psi X_{i,t} + \omega_i + \omega_t + \varepsilon_{3i,t}, \tag{16}$$

where M denotes a mediator, namely, Labour, Quality, or Innovation. $X_{i,t}$ represents the set of control variables, ϕ and ψ are the estimated coefficients on $X_{i,t}$ in Equations (15) and (16), respectively. β_1 and γ_1 are the estimated coefficients on $DO_{i,t}$ in Equations (15) and (16), respectively, while γ_2 denotes the estimated coefficients on mediators. In addition, β_0 and γ_0 in Equations (15) and (16) are interpreted in the same way as α_0 in Equation (13), and λ and ω in Equations (15) and (16) are interpreted in the same way as u in Equation. (13). $\varepsilon_{3i,t}$ and $\varepsilon_{3i,t}$ are the error term in Equations (15) and (16), respectively.

5. Results

5.1. Baseline regression analysis

Table 2 reports the results of the baseline regressions. All models control for the fixed effects of cities and years. Column (1) only considers DO. In Column (1), the estimated coefficient on DO is positive and statistically significant at the 5% level. Columns (2)–(5) add the control variables one by one; as the number of control variables included in the model increases, the sign and significance of the estimated coefficient on DO exhibit no significant changes. The coefficient value shows an upward

Table 2. Baseline results.

	ECI (1)	ECI (2)	ECI (3)	ECI (4)	ECI (5)
DO	0.0387**	0.0402**	0.0411**	0.0410**	0.0435**
	(0.0173)	(0.0174)	(0.0173)	(0.0173)	(0.0173)
Manu		0.0217	0.0473***	0.0480***	0.0489***
		(0.0162)	(0.0174)	(0.0175)	(0.0174)
Fin			0.4407***	0.4348***	0.4906***
			(0.1120)	(0.1127)	(0.1130)
FDI				0.0235	0.0261
				(0.0468)	(0.0466)
Infra					0.0009***
					(0.0002)
cons	0.3766***	0.3723***	0.3533***	0.3530***	0.3456***
	(0.0113)	(0.0118)	(0.0127)	(0.0127)	(0.0128)
year	yes	yes	yes	yes	yes
city	yes	yes	yes	yes	yes
R2	0.4624	0.4627	0.4654	0.4655	0.4690
N	3298	3298	3298	3298	3298

***: $p < 1\%$.
**: $p < 5\%$.
*: $p < 10\%$.
Source: Own processing.

trend, increasing from 0.0387 to 0.0435. The above results indicate that the agglomeration of China's AI industry has a positive impact on the ECI. The agglomeration effect generated by the AI industry is greater than the congestion effect; thus, H1 is supported. The increase in the ECI may be promoted by the clusters of China's AI enterprises. The export product complexity and the city's export value determine the economic complexity. Furthermore, the technological content of the export may be improved by AI involving more complex technology and more demanding human capital support.

From the perspective of the control variables, the results of Model (5) indicate that *Manu*, *Fin*, and *Infra* are statistically significant at the 1% level, and the coefficients are positive. These results suggest that, first, manufacturing technology upgrades and manufacturing scale expansions significantly affect economic complexity. China is regarded as a global factory due to its lower labour and land costs. The more workers in China's manufacturing industry, the more competitive the manufacturing market. Hence, companies should be incentivised to increase R&D investment and technical thresholds. The level of development of China's manufacturing industry directly determines the ECI, lending support to Lectard and Rougier (2018).

Second, the production of high-tech, high-value-added products requires considerable capital, with significant uncertainty about the success of product research. Higher financial development level may improve the level of financing and the efficiency of resource allocation. Moreover, additional funds may reduce uncertainty in enterprise development and production. Therefore, financial development may support the production of high-tech products, thereby increasing the ECI, in line with the results of Malesky and Mosley (2018).

Finally, high-tech industries and complex products require a complete infrastructure due to the high degree of collaboration needed in the industry chain (Martín &

Fernández, 2022). Complete infrastructure construction may reduce corporate inventory and improve corporate logistics efficiency. Hence, companies could reduce production and transportation costs, which allows companies to have sufficient funds to produce and develop high-tech and complex products to enhance the ECI, in line with the results of Hidalgo and Hausmann (2009). The estimated coefficient on FDI is positive but not significant. This result is consistent with the conclusions of some previous investigations (Lectard & Rougier, 2018) but does not support the findings of Ozsoy et al. (2021). We suggest that foreign capital inflow may affect China's technological improvement in the short term. However, it is likely to restrain the progress of China's independent innovation capability in the long term, implying that the ECI is not affected by FDI.

5.2. Analysis of heterogeneity of spatial agglomeration

The economic development conditions and development levels of various regions in China differ substantially, so enterprises are affected differently by AI industry agglomeration across regions. Economic complexity exhibits substantial heterogeneity across regions. Based on the classification standards of the National Bureau of Statistics of China, the country is divided into eastern, central, and western regions based on economic development conditions and development levels. Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, and Zhejiang provinces are the eastern regions; Anhui, Henan, Heilongjiang, Hubei, Hunan, Jilin, Jiangxi, and Shanxi provinces are the central regions; Chongqing, Guizhou, Gansu, Guangxi Zhuang Autonomous Region, Inner Mongolia Autonomous Region, Ningxia Hui Autonomous Region, Tibet Autonomous Region, Xinjiang Uygur Autonomous Region, Qinghai, Shanxi, Sichuan, and Yunnan provinces are the western regions.

Table 3 reports the regression results for the whole of China, as well as the eastern, central, and western regions. The estimated coefficient on DO in the western region is not significant. AI industry agglomeration in the western region has almost no impact on the ECI. We suggest that the western region lacks natural resources and is characterised by a remote location, backward economic development, severe brain drain, and limited development of the AI industry. Hence, the AI industry has not formed a significant agglomeration effect.

However, the estimated coefficient on DO in the eastern and central regions is significantly positive, and the estimated coefficient in the central region is more significant than that in the eastern region. This result implies that AI industry agglomeration has a substantial and positive effect on the ECI in the eastern and central regions. Compared with the eastern region, the agglomeration of the central AI industry has a more significant impact on the ECI. The cities in the eastern area experience congestion due to the overcrowded AI industrial cluster. As the clustering of AI businesses continues, land and labour costs in the eastern area grow, and several industries relocate to the central and western regions. The central area has a distinct geographical advantage, abundant natural resources, well-developed transportation, competitive labour forces, and solid industrial foundations (Yuan

Table 3. Heterogeneity results from spatial agglomeration.

	ECI overall	ECI east	ECI central	ECI west
DO	0.0435**	0.0281*	0.0903***	−0.0052
	(0.0173)	(0.0158)	(0.0302)	(0.0509)
Manu	0.0489***	0.0199*	0.1187***	0.2227***
	(0.0174)	(0.0124)	(0.0366)	(0.0749)
Fin	0.4906***	0.4054***	0.5874**	0.2995
	(0.1130)	(0.0825)	(0.2313)	(0.4175)
FDI	0.0261	0.0865***	−0.1043	0.0137
	(0.0466)	(0.0304)	(0.1441)	(0.2508)
Infra	0.0009***	0.0001***	0.0014***	0.0012***
	(0.0002)	(0.0002)	(0.0005)	(0.0004)
cons	0.3456***	0.4737***	0.3290***	0.3290***
	(0.0128)	(0.0091)	(0.0183)	(0.0183)
year	yes	yes	yes	yes
city	yes	yes	yes	yes
R2	0.4690	0.7654	0.4063	0.3632
N	3298	1462	1156	678

***: $p < 1\%$.
**: $p < 5\%$.
*: $p < 10\%$.
Source: Own processing.

et al., 2020). Consequently, the central area plays an essential role in large-scale industrial transfer inside China, resulting in a complete industrial chain, which improves the ECI. As a result, the AI industry clustering in the central region results in robust economic dynamism.

5.3. Endogeneity

Theoretical research has shown a mutual influence between AI industry agglomeration and the ECI, generating potential endogeneity (Hidalgo, 2021; X. Wang et al., 2021). Endogeneity may stem from self-selection. Companies with high product complexity may automatically choose regions characterised by the net effect of high agglomeration in the AI industry (X. Wang et al., 2021). Second, AI industry agglomeration may promote an increase in the ECI. However, cities with complex export products usually have more developed high-end manufacturing and a more substantial R&D and innovation atmosphere. They are more attractive to high-end talents; hence, there may be a reverse causal relationship between AI industry agglomeration and the ECI. Endogeneity may lead to biased estimation results. To deal with possible endogeneity, this study uses instrumental variable estimation.

Angrist and Pischke (2010) have pointed out that a suitable instrumental variable must simultaneously satisfy the relevance and exogeneity conditions. In other words, instrumental variables must explain the changes in the degree of agglomeration of the AI industry, but they cannot directly or indirectly affect the ECI through other means. In general, instrumental variables related to industrial agglomeration are based on geographic or historical perspectives (Ciccone, 2002; Hidalgo, 2021). On the one hand, since some geographic indicators are naturally formed, and some historical indicators refer to distant periods, they may better satisfy the exogeneity condition.

Table 4. Endogeneity test.

	ECI (1)	ECI (2)
DO	0.5255***	0.7161***
	(0.0833)	(0.0802)
Manu	0.1052***	0.1095***
	(0.0103)	(0.0112)
Fin	0.8082***	0.8559***
	(0.0922)	(0.0995)
FDI	−0.0081	−0.0460
	(0.0452)	(0.0488)
Infra	-.0001	0.0001
	(0.0001)	(0.0001)
cons	0.3506***	0.3372***
	(0.0102)	(0.0105)
Kleibergen-Paap rk LM statistic	79.396	141.970
	0.0000	0.0000
Cragg-Donald Wald F statistic	24.057	74.564
Kleibergen-Paap rk Wald F statistic	29.646	76.612
R^2	0.2240	0.0931
observations	3298	3298

***: $p < 1\%$.
**: $p < 5\%$.
*: $p < 10\%$.
Source: Own processing.

On the other hand, geographical or historical indicators are likely related to the current economic system's indicators, thus meeting the relevance condition.

In terms of historical variables, in line with Ciccone (2002), we use the presence or absence of a railroad in the city in 1933 and the population density of the city in 1984 as instrumental variables. In terms of geographic variables, following Barone et al. (2015), this study employs the geographic slope of the city as the instrumental variable. We use the two-step optimal GMM for estimation.

Model (1) in Table 4 includes the city's geographic slope and population density in 1984 as the instrumental variables. Model (2) in Table 4 includes the geographic slope of the city and the presence or absence of a railroad in the city in 1933.

Overall, the results in Table 4 show that both the Kleibergen-Paap rk LM test and the Cragg-Donald Wald F test reject the null hypothesis of insufficient and weak instrumental variable identification, indicating satisfactory relevance.

After considering endogeneity, the estimated coefficients on DO are all positive and significant at the 1% level. When using the city's geographic slope and population density in 1984 as instrumental variables, the estimated coefficient on DO is 0.5255. When using the geographic slope of the city and the presence or absence of a railroad in the city in 1933 as instrumental variables, the estimated coefficient on DO is 0.7161. Both coefficients are significantly higher than that of the benchmark regression (0.0435).

Overall, after addressing endogeneity, the AI agglomeration significantly increases the ECI. Furthermore, the agglomeration effect is greater than that of the benchmark regression. In other words, the positive externalities generated by China's AI industry agglomeration are more significant than the negative externalities; hence, H1 is supported

5.4. Robustness analysis

Existing studies have shown that the special administrative status of Chinese cities may exert administrative power on factor agglomeration and economic development, and the agglomeration effect of the AI industry is not comparable across municipalities, sub-provincial cities, and ordinary prefecture-level cities (J. Wang & Yeh, 2020). China has four first-tier cities and 15 sub-provincial cities (J. Wang & Yeh, 2020). Therefore, we analyse the different effects of AI industry agglomeration in these contexts.

First, we exclude four first-tier cities in China from the regression analysis. We report the empirical results in Column (2) of Table 5. Second, we exclude 15 sub-provincial cities in China from the regression analysis, and the results are reported in Column (3) of Table 5. Overall, the results show that the estimated coefficients on AI industry agglomeration are positive and significant at 0.0442 and 0.0443, respectively, consistent with the benchmark regression results, further supporting H1.

5.5. Mechanism test

According to the above empirical results, DO significantly increases the ECI. However, the internal mechanism through which AI industry agglomeration promotes the ECI requires further investigation. Based on the industrial agglomeration externality theory of (Marshall, 2009), we contend that AI industry agglomeration may increase the ECI through people, goods, and knowledge.

5.5.1. Mediating effect of the per capita human capital in the labour market

The study's results indicate that per capita human capital in the labour market mediates the relationship between AI industry agglomeration and the ECI. However, AI

Table 5. Robustness test.

	ECI overall	ECI Excluding first-tier cities	ECI Excluding sub-provincial cities
DO	0.0435**	0.0442**	0.0443**
	(0.0173)	(0.0175)	(0.0184)
Manu	0.0489***	0.0503***	0.0579***
	(0.0174)	(0.0177)	(0.0188)
Fin	0.4906***	0.5067***	0.4766***
	(0.1130)	(0.1169)	(0.1196)
FDI	0.0261	0.0185	0.0184
	(0.0466)	(0.0484)	(0.0526)
Infra	0.0009***	0.0009***	0.0008***
	(0.0002)	(0.0002)	(0.0002)
cons	0.3456***	0.3448***	0.3455***
	(0.0128)	(0.0130)	(0.0133)
year	yes	yes	yes
city	yes	yes	yes
R^2	0.4690	0.4648	0.4534
N	3298	3,230	3,043

***: $p < 1\%$.
**: $p < 5\%$.
*: $p < 10\%$.
Source: Own processing.

Table 6. Regression results of the mediating effect of the per capita human capital in the labour market.

	ECI (1)	Labour (2)	ECI (3)
DO	0.0435**	0.7459***	0.0356**
	(0.0173)	(0.2539)	(0.0171)
Labour			0.0106***
			(0.0012)
Control variables	yes	yes	yes
year	yes	yes	yes
city	yes	yes	yes
R^2	0.4690	0.4878	0.4818
N	3298	3,298	3,298

***: p < 1%.
**: p < 5%.
*: p < 10%.
Source: Own processing.

industry agglomeration is positively related to per capita human capital in the labour market (see Model 2 in Table 6) and positively impacts the ECI (see Model 1 in Table 6). In addition, the per capita human capital in the labour market is positively associated with the ECI (see Model 3 in Table 6). The coefficient on AI industry agglomeration decreases when the per capita human capital in the labour market is considered in Model 3. Therefore, H2 is supported. The results show that the AI industry clustering directly affects the ECI through per capita human capital in the labour market. Increasing the degree of AI industry agglomeration promotes high-level talent gathering and low-end labour substitution (Acemoglu & Restrepo, 2019; Marshall, 2009), increasing the per capita human capital in the labour market. Clustering AI enterprises in certain cities may attract highly educated talent through greater economic development, higher salaries, and a better entrepreneurial environment. As an agglomeration effect, gathering high-level talent may help enterprises improve their production capability and efficiency and develop new and high-tech products. Moreover, cities with a more significant proportion of high-level labourers may fully exploit the positive externalities of the AI industry agglomeration, thus developing more products and producing more complex goods. Hence, the per capita human capital in the labour market is an essential path for AI industry agglomeration to increase the ECI.

5.5.2. Mediating effect of intermediate input products quality

The study's results indicate that intermediate input product quality does not mediate the relationship between AI industry agglomeration and the economic complexity of the city. AI industry agglomeration has no significant impact on intermediate input product quality, as the coefficient on AI industry agglomeration is not statistically significant (see Model 2 in Table 7). However, the coefficient on AI industry agglomeration does not decrease (see Model 3 in Table 7). Thus, H3 is not supported. This result contradicts Ellison et al. (2010).

There may be several reasons why AI industry agglomeration does not affect intermediate input product quality. On the one hand, the clustering of AI companies causes excessive competition in the intermediate product market. Enterprises squeeze

Table 7. Regression results of the mediating effect of intermediate input products quality.

	ECI (1)	Quality (2)	ECI (3)
DO	0.0523***	0.0346	0.0530***
	(0.0181)	(0.0319)	(0.0181)
Quality			−0.0232**
			(0.0106)
Control variables	yes	yes	yes
year	yes	yes	yes
city	yes	yes	yes
R^2	0.4836	0.1274	0.4844
N	3,040	3,040	3,040

***: $p < 1\%$.
**: $p < 5\%$.
*: $p < 10\%$.
Source: Own processing.

each other's market space and potential and implement low-price competition strategies, significantly reducing their profit space. Hence, the R&D funds of enterprises will decrease due to fierce price competition. On the other hand, the agglomeration of AI companies may cause fierce competition in factors market. The agglomeration of AI companies has triggered a large-scale increase in demand for some production factors and a substantial increase in production factor costs, increasing the production costs. Thus, the enterprise's production profit and funds for improving the quality of the intermediate product are expected to decrease. Hence, the improvement in intermediate input product quality is not a channel for AI industry agglomeration to promote an increase in the ECI.

5.5.3. Mediating effect of innovation and entrepreneurship quality

The study's results also show that innovation and entrepreneurship quality mediate the relationship between AI industry agglomeration and the ECI. On the one hand, AI industry agglomeration is positively associated with innovation and entrepreneurship quality (see Model 2 in Table 8) and positively influences the ECI (see Model 1 in Table 8). On the other hand, innovation and entrepreneurship quality are positively associated with the economic complexity index (see Model 3 in Table 8). The coefficient on AI industry agglomeration decreases from 0.0442 to 0.0292 when innovation and entrepreneurship quality are included in Model 3. Thus, H4 is supported. The results indicate that the AI industry clustering directly affects the ECI via innovation and entrepreneurship quality. We contend that the clustering of AI enterprises increases innovation and entrepreneurship quality for several reasons. First, the AI industry is knowledge- and technology-intensive, promoting local high-tech industries' development. Second, AI industry agglomeration generates knowledge and technology spillover through information sharing and mutual learning. Finally, the clustering of AI enterprises may reduce R&D innovation costs. Hence, we suggest that improving the agglomeration level of the AI industry enhances innovation and entrepreneurship quality. High-quality innovation allows enterprises to develop products with unique, high value-added, and high technological complexity. This study also shows that AI industry agglomeration directly promotes the ECI (based on the

Table 8. Regression results of the mediating effect of innovation and entrepreneurship quality.

	ECI (1)	Innovation (2)	ECI (3)
DO	0.0442**	0.1654***	0.0292*
	(0.0175)	(0.0465)	(0.0170)
Innovation			0.0908***
			(0.0066)
Control variables	yes	yes	yes
year	yes	yes	yes
city	yes	yes	yes
R^2	0.4648	0.0259	0.4960
N	3,230	3,230	3,230

***: $p < 1\%$.
**: $p < 5\%$.
*: $p < 10\%$.
Source: Own processing.

baseline model). Hence, improving innovation and entrepreneurship quality is a vital channel for AI industry agglomeration to promote the ECI.

6. Discussion and conclusions

6.1. Conclusions

The integration of AI technology with other industries has deepened in China, reconstructing various economic activities such as production, distribution, exchange, and consumption (Furman & Seamans, 2019; Martínez et al., 2022). Many studies have analysed the factors affecting the ECI from the perspectives of factor endowments (Z. Wang & Wei, 2010), FDI (Antonietti & Franco, 2021), the global value chain division of labour (Dai & Jin, 2014), and spatial agglomeration (Balland et al., 2020; Malesky & Mosley, 2018; Storper, 2018). However, few studies have focused on the impact of AI on the ECI. To fill this gap in research, this study investigates the causal relationship between AI industry agglomeration and economic complexity in 194 Chinese cities from 2000 to 2016.

First, we build a novel dataset including China's 2,503,795 AI enterprises using the web crawling technique. In addition, we use the DO index developed by Duranton and Overman (2005) to measure the agglomeration of AI enterprises in 194 Chinese cities from 2000 to 2016, avoiding the modifiable areal unit problem. Second, we use the method of reflection proposed by Hidalgo and Hausmann (2009) to measure the ECI of the sample cities based on UN Comtrade and China Customs Data. Third, we employ a panel regression model to investigate the relationship between AI industry agglomeration and the ECI. In addition, we use several instrumental variables, such as the presence or absence of a railroad in the city in 1933, the population density of the city in 1984, and the geographic slope of the city to deal with potential endogeneity. Finally, we propose a mediating model to study the inner mechanism of action in the relationship between AI industry agglomeration and the ECI from the perspective of the Marshall industry agglomeration theory.

We find a positive impact of AI industry agglomeration on the ECI in China. Moreover, manufacturing development, financial development, and infrastructure are positively related to the ECI. Unexpectedly, FDI had no significant effect on the ECI.

We argue that the inflow of foreign capital may affect China's technological improvement in the short term, but it is likely to restrain the improvement of China's independent innovation capability in the long term. The effect of FDI on economic complexity should be discussed in future studies, as the FDI inflow may produce technological spillover and competition effects. Consequently, the government should invest more resources to enhance manufacturing, finance, and infrastructure. FDI should be strictly controlled in terms of content and form, especially in the eastern regions, where competition is fierce.

Furthermore, we show that China's AI industry has an asymmetric spatial agglomeration effect. We observe a positive impact on the ECI in the eastern and central regions. Interestingly, AI industry agglomeration in the western region has almost no effect on the ECI. We suggest that the western region lacks natural resources and is characterised by remote locations, backward economic development, severe brain drain, and limited development of the AI industry. Western areas have not experienced a significant agglomeration effect in the AI industry. To promote the agglomeration of the AI industry, the formation of agglomeration effects in the western region should accelerate. However, preventing excessive agglomeration and congestion in eastern and central regions is also crucial.

We also find that per capita human capital in the labour market as well as innovation and entrepreneurship quality mediate the relationship between AI industry agglomeration and the ECI. AI agglomeration facilitates the gathering of high-end talents and increases per capita human capital in the labour market, helping develop more various and complex products. Similarly, AI industry agglomeration improves innovation and entrepreneurship quality. High-quality innovation and entrepreneurship help companies form innovative ideas and develop high-tech products. However, we find that intermediate input product quality is not a channel for AI industry agglomeration to promote an increase in the ECI, in contrast to Ellison et al. (2010) and the theory of Marshall (2009). We argue that the clustering of AI enterprises causes excessive competition in the intermediate product market. When the funds for R&D decrease, the intermediate input product quality does not increase following the agglomeration of the AI industry. High-end talent and high-quality innovation should complement AI industry agglomeration to fully exploit the positive agglomeration externalities. The government should use AI industrial policies to strengthen the import guidance of intermediate input products, thus promoting economic complexity.

6.2. Contributions

This study makes three primary contributions to the literature. The first contribution lies in measuring AI industry agglomeration at the city level in China. Since the AI industry is emerging, related data are lacking. We use a novel dataset including China's 2,503,795 AI enterprises to overcome these limitations. These new data enrich the available information on Chinese AI enterprises.

Second, this study extends previous research on the determinants of the ECI. Our findings reveal a relationship between AI and economic complexity. Previous studies have mainly focused on the factors that affect economic complexity, such as factor endowments, spatial agglomeration, the global value chain division of labour, and FDI. Our work provides a new perspective for studying the determinants of product complexity and economic complexity.

Finally, we develop a theoretical framework to examine the inner-impact mechanism in the relationship between the AI industry clustering and economic complexity. Although Marshall (2009) contends that industrial agglomeration may form relevant externalities through people, goods, and knowledge, our findings are slightly different. We find that the goods path is not a channel for AI industry agglomeration to promote an increase in the ECI. There are three potential reasons for the different results. First, we argue that the clustering of AI enterprises is more likely to cause excessive competition in the Chinese intermediate product market; hence, there are no increasing returns from intermediate product sharing. Second, high-end talents are not equally distributed across a city in China due to uneven economic and social development; thus, intermediate products cannot be fully utilised. Finally, the agglomeration of China's AI enterprises is promoted by the government rather than naturally achieved. Administrative divisions and local governments significantly interfere with the development of the AI industry clusters. The agglomeration level of AI in most cities is low, and AI enterprises' positive agglomeration effects cannot be fully realised.

6.3. Limitations and further research

Despite its contributions, this study has several limitations. Our investigation is based on prefecture-level city information as most data at the city level in China is available at the prefecture-level. Future studies should address the county or district level. Moreover, the data used for calculating economic complexity are only updated until 2016. However, since the development of the AI industry has changed significantly from 2016 to 2021, further testing is necessary. Finally, future studies should use additional indicators to measure people, goods, and knowledge.

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