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Spatiotemporal distribution and dynamics evolution of artificial intelligence development in China☆

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ABSTRACT

The quantified measurement and comprehensive analysis of artificial intelligence development (AIDEV) are vital for countries to form AI industrial ecology and promote the long-term development of regional AI technology. Based on the innovation ecosystems (IE) theory, this paper constructs an evaluation system to measure and analyze the spatiotemporal distribution and dynamic evolution of the AIDEV in China from 2011 to 2020. The results show that the AIDEV of China presents an overall upward trend and an obvious unbalance in the spatial distribution which is "eastern > central > western". Meanwhile, the provinces of low-level AIDEV are catching up with the high-level provinces, which leads to the regional difference of AIDEV narrowing. Moreover, the concentration and polarization phenomenon of AIDEV in China has been weakening and the AIDEV will continue to increase in the next three years. Further, there is a significantly positive spatial autocorrelation of AIDEV. Finally, high AIDEV provinces will increase the probability of surrounding provinces' AIDEV to develop. This paper expands the research stream in the field of AI research, extends the application scenarios of IE theory, and puts forward some relevant policy recommendations.

1. Introduction

The impact of the new generation of information technology on the economy, society, and environment piqued the interest of many [1–3]. Among these, representative artificial intelligence (AI) technology has become an engine to the new generation of scientific revolutions and industrial upgrading [4,5]. It has permeated through all areas of human society [6–8]. Considering the revolutionary effects of AI applications, countries worldwide have begun to vigorously develop AI [9] and have made AI development as their national strategic direction [5]. However, the development of AI still faces several challenges [10]. First, the investment market is unstable. Specifically, private investment in the global AI sector decreased for the first time in a decade [11]. Second, AI applications have been hindered. Specifically, the proportion of companies adopting AI has stagnated in recent years [11]. Third, there are large gaps in the AI development levels across regions owing to differences in regional economic, industrial foundation, and technology levels [12].

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Considering China as an example, the AI technology in China has developed rapidly with the support of the government [13] and is currently leading in the AI competition [14]. However, there are still problems with the development of AI. After 2016, due to the shortage of funds and talent, the number of newly established AI enterprises gradually decreased and 94.55 % of enterprises with AI patents greater than 100 were concentrated in 5 provinces of China in 2021 [15]. These issues will affect the long-term development of AI technology and AI industry. Therefore, considering AI is a critical factor for countries seeking competitive advantages in the age of new generation of scientific revolution and industrial upgrading, promoting the long-term development of AI has become a global priority [16].

In such cases, a comprehensive evaluation and analysis of the regional AI development (AIDEV) is imminent. From the perspective of economic development, measuring the AIDEV and conducting a detailed analysis of its spatiotemporal distribution and dynamics evolution status are economically advantageous for promoting the long-term development of the AI industry in various regions. From a political perspective, it serves to evaluate the effectiveness of previous policy implementations and formulate future policies. It also serves as the data foundation and decision-making basis for AIDEV's quality evaluation, feedback, and early warning system. Existing research has begun to use evaluation systems or data on AI patents, robots, and other factors to measure the level of regional AI development [13,17,18]. Although previous studies have made some contributions, research gaps remain.

First, the extant literature primarily uses industrial robots or AI patents as alternative variables to measure the level of regional AI development [19,20]. While most of the AI evaluation systems lacked theoretical support or failed to comprehensively measure the AI development foundation, process, and outcomes [21,22]. Whether measured using a single surrogate variable or an evaluation system lacking theoretical support, their measurements cannot comprehensively and scientifically reflect the region's AI development status, affecting the study's accuracy.

Second, previous studies have primarily focused on the level of AI development at country or enterprise levels [22,23]. National-level research can only reflect the overall level of AIDEV in the country from a macro perspective [11,15], and enterprise-level research can only focus on the impact of AI applications on production and business operations within a specific company [23,24]. Because of the limitation of data, little research has been done to explore the regional level (such as the provincial level) which is critical for understanding each region's development status and promoting the AIDEV.

Third, existing AI measurement studies have primarily investigated the impact or relationship of AI adoption on social and economic issues [25–27]. Currently, there is still a lack of research focusing on the development status of AIDEV. In particular, the spatiotemporal distribution and dynamics evolutionary characteristic of AIDEV in a specific country (e.g., China) remain to be studied. Given that China is the leading country in AI development, investigating the AIDEV in China has a high reference value for both literature and practice.

Accordingly, to fill the above gaps in previous studies based on innovation ecosystem (IE) theory, this paper constructs an evaluation system to measure AIDEV. Subsequently, by selecting China as the research object, we collect AI-related data and calculate the provincial AIDEV in China from 2010 to 2020. Following this, we analyze the spatiotemporal characteristic, regional difference, spatial correlation, dynamic evolution of AIDEV in China. The contributions of this paper can be summarized in the following ways.

First, we propose the concept and specific definition of AIDEV as a series of socioeconomic activities that contribute to the formation of an AI industrial ecology and promote the long-term development of regional AI technology. This fills the gap in previous AI-related studies that only focused on the impact of social and economic issues [28,29], but lacked research on the AI development itself, which is important for the long-term and healthy development of regional AI technology and industry.

Second, we scientifically and comprehensively evaluate the AIDEV. In this study, we apply the IE theory and construct the AIDEV conceptual framework to highlight the synergy of muti-participation in pushing AIDEV which expands the application scenarios and research topics of the IE theory [30,31]. Based on this conceptual framework, we propose an evaluation system. This fulfills a research gap in most of the previous studies that used a single alternative variable to measure AIDEV, which could affect the measurement accuracy [25,29], or lacked a scientific evaluation system which was based on theoretical support [17,21]. Our evaluation system and measurement results offer important insights and provide a statistical measurement method for future studies that measure the AI development and explore its socio-economic impacts.

Third, we contribute to the research stream by fully displaying the spatial and temporal structural characteristics of China's AIDEV at the provincial level, which is vital for understanding the development status of AIDEV in China and expanding the research perspective in AI research [15,16,23]. Based on the research results, the Chinese government can formulate more scientific and targeted policies to promote the long-term development of the AI industry. On this basis, we introduce a research path of "evaluation system construction-data collection-measurement-spatiotemporal distribution and dynamics evolution analysis" which can be used for studying other advanced technologies.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 develops the construction of an evaluation system and data sources. Section 4 introduces the methods used in this study. Section 5 presents the description of empirical analysis and the analysis of the research results. The conclusions and discussions are presented in Section 6.

2. Literature review

2.1. Research on AI development and measurement

The existing research on AI development and measurement can be divided into two main categories. The first mainly describes the development of AI in various countries and regions from multiple dimensions or using evaluation systems in the form of research reports. In the developed world, Stanford University tracks and analyzes the AI development of countries and regions worldwide in terms of R&D, technical performance, technical AI ethics, etc. [11]. The Joint Research Center developed an evaluation system for 22 indicators and facilitated the evaluation of the international and European comparisons in the AI domain [12]. Muro and Liu set two first-level indicators, namely, AI R&D activities and commercialization activities to evaluate and analyze the AI development of 384 cities [22].

In China, the Blue Book of World AI Industry Development analyzes the development of AI industry worldwide in four dimensions: industrial development environment, technological environment, AI enterprises, and investment and financing [32]. In the China AI Industry Development Index, the development of AI industry is evaluated from basic support, innovation ability, integrated application, industrial operation, and environmental safeguard [33]. While the development of AI in G20 member countries is evaluated from four first-level indicators: basic support of AI, innovative resources and environment, scientific and technological research, and industry and application [34].

The second type of study primarily uses a single alternative variable that can reflect AI technological innovation, industrial development, or application level to measure the AI development, such as industrial robots and AI-related patents. Only a few studies have measured and calculated the AI development using evaluation systems.

Industrial robot data is one of the most widely used alternative variables for AI measurement. Acemoglu and Restrepo first used the industrial robots to study the effect of AI on labor [25]. Based on their practice, scholars have widely used the industrial robots as a substitute for AI to study the influence of AI on technological innovation [5], discuss the influence of AI application in energy sectors [26], prove that the AI adoption could improve the energy efficiency in manufacturing enterprises [35], examine the effect of AI on green total factor productivity (GTFP) and economic growth [28], and investigate how AI affects carbon intensity [29]. In terms of patents, many scholars have used keyword retrieval methods to identify AI-related patents and evaluate the local AI development based on the number and characteristics of patents. Abadi and Pecht evaluated the application and development of AI in leading countries and companies worldwide based on AI-related patents [36]. Zou and Xiong collected patents containing AI keyword information from 285 cities in China to study whether AI can promote industrial upgrading [13]. Similarly, Yang identified AI-related patents to examine their impact on firms' productivity and employment [23].

Most studies that use evaluation systems for measurement are relatively simple and lack a theoretical foundation. For example, Dong et al. built an AI comprehensive evaluation index system that measured three dimensions: public attention, technology and science education level, and market attention [21]. Ma et al. developed an index system to evaluate AI, including hardware, educational research, and data [17]. Basically, current studies on AI measurement and development have been analyzed from the technical aspect, industrial aspect, scientific aspect, and educational aspect. However, in research reports, most studies only provide descriptive analysis of AI development based on data, without quantitatively measuring the regional AIDEV. In research paper, the practice of measuring AI development using alternative variables or evaluation systems lacking theoretical support raises issues of insufficient comprehensive measurement and lack of scientificity.

2.2. Innovation ecosystem theory

The innovation ecosystem (IE) theory is of growing significance to the literature on innovation, business, and economics. It is a concept that is analogized from biology and adopted in business studies by Moore [37], who was the pacesetter in introducing the term "business ecosystem". Based on this, Adner [38] and Adner & Kapoor [39] further integrated the concept into innovation studies and strongly contributed in disseminating the term "innovation ecosystem" [40]. Since then, research on IE has become popular and scholars have proposed various definitions of IE based on their different focuses and purposes [41], forming different IE subdivision concepts, such as open innovation ecosystem [30], digital innovation ecosystem [42], platform-based innovation ecosystem [43], and regional innovation ecosystems [31].

Although most of the definitions of IE are relatively abstract [44], they focus primarily on collaborations and interdependence among diverse actors and artifacts (e.g., products, services, resources, and technologies) [45,46]. In view of this, the IE we refer to in this study stems from Jackson's [47] study, which addresses IE as the relationship between actors to achieve technological development and innovation. Accordingly, the definition and characteristic of IE theory makes it a promising framework for studying AIDEV. As mentioned previously, we define the regional AIDEV as the AI technological development and industrial ecology resulting from the dynamic interaction and cooperation of the local AI industrial enterprises, governments, universities, and other entities which is in line with the definition of an IE [47]. However, the existing literature mostly measures the AIDEV based on a feature that reflects the AIDEV, ignoring the synergy of muti-participation in pushing the AIDEV (e.g., Liu et al. [26] and Liu et al. [35]). Therefore, the introduction of IE theory into AIDEV measurement, which indicates considering regional AIDEV as an IE, can highlight the interaction between entities that promote AI development, and help to comprehensively measure the innovation environment and actors that participate in promoting AIDEV.

3. Evaluation system establishment and data sources

3.1. Evaluation system establishment

To measure the AIDEV, it is necessary to clearly define its scope. In this study, we define that AIDEV is a series of socioeconomic activities that form an AI industrial ecology and promote the long-term development of regional AI technology which is driven by the AI technology innovation and application. These socioeconomic activities are generated through the cooperation, dynamic interaction, and co-evolution among AI industry, government, scientific research institutions, universities, and other entities. Moreover, AIDEV requires the rational and effective use of development resources and the formulation of strategies to realize the coordination and unity of economic value and social benefits, technological innovation and promotion, current benefits and long-term development.

First, AI is a cluster of smart technologies, consisting of machine learning, natural language processing, robots, etc. [48]. As a result, the AIDEV is a type of technological innovation and development, therefore, the measurement of AIDEV needs to highlight its technological application and innovation level. Secondly, AIDEV is not only the development of AI technology, but also the development of regional AI industry ecology, which indicates that each AI-related actor cooperates and interacts dynamically with each other under the support of specific development resources and development strategies. Therefore, the measurement of AIDEV must focus not only on industrial activities and economic benefits in the region, but also on the social resources and development strategies that promote the AIDEV. Finally, adapted from the concept of sustainability, the AIDEV requires the regional AI development not only to meet the current socio-economic needs but also to prioritize long-term development in the future. Because AI is an emerging industry, research and data are limited. For this reason, measuring AIDEV reasonably and quantitatively and obtaining relevant data have become difficult in the relevant research [5,13].

The characteristic of innovation ecosystem (IE) theory makes it a promising framework for explaining AIDEV. In Jackson's [47] study, IE is the relationship between actors to achieve technological development and innovation. The introduction of IE theory into AIDEV measurement, which indicates considering regional AIDEV as an IE, can highlight the interaction between entities that promote AIDEV, and help comprehensively measure the innovation environment and actors that participate in promoting AIDEV. Therefore, based on the IE theory, this paper proposes a new conceptual framework of a four-quadrant division for measuring the AIDEV.

As shown in Fig. 1, to begin with, this paper regards the regional AIDEV as an IE composed of various actors. According to Jackson's [47] theory, actors should include material resources, human capital, institutional entities, and government investments. Consequently, we incorporate these factors into the conceptual framework and classify them based on the innovation resources system, innovation policy system, innovation activities, and innovation achievement. With the support of innovation resources and policy system, each actor cooperates and evolves with each other, participates in innovation activities, and finally achieves innovation. Following this, these four innovation dimensions are extended to four development-related indicators, namely development foundation, development strategy, development activities, and development quality, and they are divided into four quadrants. In this four-quadrant coordinate axis, the line from bottom left to top right represents the time dimension, that is, from now to the future, and the line from top left to bottom right represents the process dimension, that is, from action to result.

In terms of the time dimension, development foundation and activities are the existing development resources and current development activities, respectively, while development strategy and development quality represent the future-oriented development plan and development potential, respectively, which are both important conditions for the long-term development. Thus, AIDEV not only emphasizes the current AI development but also emphasizes how to promote the long-term development of future AI technologies under existing resources and conditions. In terms of the process dimension, development strategy and development activities denote the actions taken by various actors to achieve development; development foundation is the development resources generated and

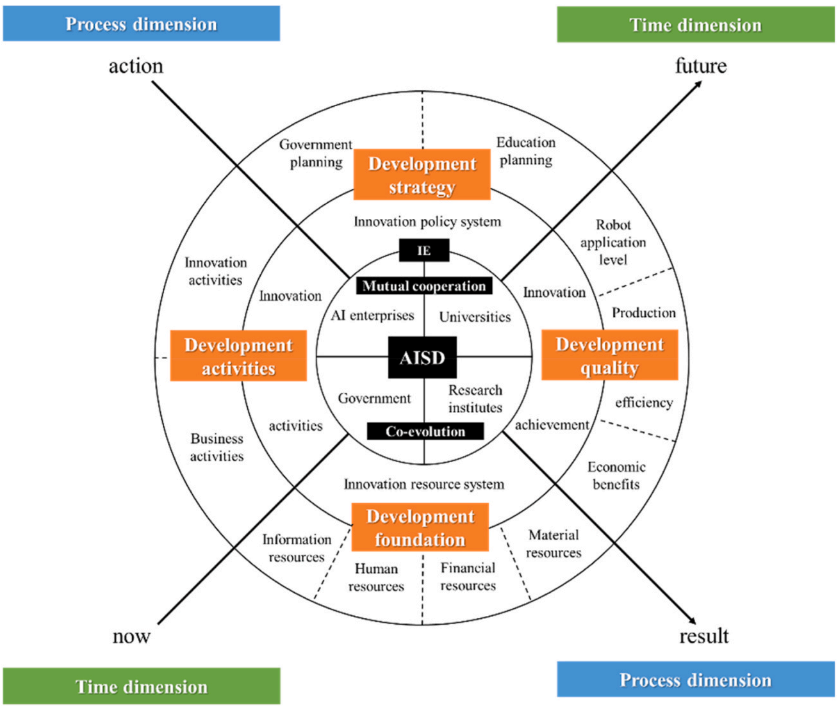

Fig. 1. Concept framework of AIDEV measurement based on IE theory.

accumulated by development actions and strategies, while the development quality stands for the development achievement.

Further, based on the principles of scientificity, representativeness, and data availability, we refine the conceptual framework and develop it into an evaluation system with four primary indices (development foundation, development strategy, development activities, and development quality), 11 secondary indices and a total of 15 tertiary indices, shown in Table 1. Learning from previous studies [11,12], our evaluation system comprehensively estimates the AIDEV from the perspective of economy, education, scientific research, and technology. Moreover, this evaluation system overcomes the limitation of prior studies which were mostly restricted to simply evaluating the AI based on development results [21] or development activities [22]. Instead, we innovatively propose a four-quadrant division method, that leads to a complete investigation of the AIDEV from the time dimension and process dimension. The definitions and structures of these four primary indices are as follows.

Development foundation reflects the productive factors and the necessary resources that directly or indirectly support and promote the long-term development of AI technology and industry. This paper selects four indicators: human resources, financial resources, material resources, and information resources. To start with, human resources are the most critical resource to promote industry development [49]. Therefore, this paper uses the AI talent scale index, which is measured as the number of R&D personnel in the local AI industry divided by the permanent resident population at the end of the year. Besides, the tertiary index AI R&D investment is chosen to explain the financial resources in development foundation and it is reflected by the ratio of total R&D expenses in the local AI industry to local GDP. Restricted by enterprises' financial resources, the R&D investment reflects the adequacy of these resources to a certain extent [50]. What's more, material resources mainly reflect the means of production required for AIDEV, including buildings, instruments and equipment, raw materials, energy, etc. Hence, instruments and equipment, and information infrastructure are adopted to reflect the material resources in the development foundation. Specifically, instruments and equipment and information infrastructure are measured by the instrument and equipment expenditures of each R&D personnel and investment in fixed assets in the local AI industry, respectively. In addition, the long-term development of AI technology and industry cannot be separated from the large amounts of data to provide a training set for model training and algorithm optimization [51]. Therefore, learning from Ma et al.'s study [17], we use the data foundation to represent the information resource, which is measured by the number of local Internet broadband subscribers, considering that the greater the number of Internet broadband subscribers, the greater the amount of data they generate, which to some extent, reflects the increase in data required for algorithm optimization.

Development strategy reflects the attention of the local government paid to the long-term development of AI, as well as its investment and planning. This paper selects two indicators including government planning and education planning to reflect the development strategy. On the one hand, the government supports the development of AI by formulating thoughtful and proactive policies that will further promote the long-term development of AI [52]. Therefore, we use policy emphasis to measure government planning. The policy emphasis in this paper is measured by the number of times that "intelligence," "robot," "artificial intelligence," and other AI-related keywords are mentioned in the annual work report of local government. On the other hand, the government's support for AI is also reflected in its investment and support for AI education. Therefore, subject construction in higher education is

Table 1
Evaluation system and index weight of AIDEV.

Primary index	Secondary index	Tertiary index	Indicator meaning	Weight	Total
Development foundation (A)	Human resources (A1)	AI Talent scale	Total number of R&D personnel in local AI industry/permanent resident population at the end of the year	0.0759	0.2976
	Financial resources (A2)	AI R&D investment	Total R&D expenditure of local AI industry/local GDP	0.0618	
	Material resources (A3)	Instrument and equipment	Total instrument and equipment expenditure of local AI industry/number of R&D personnel in local AI industry	0.0561	
		Information infrastructure	Total fixed asset investment in local AI industry	0.0902	
	Information resources (A4)	Data foundation	Number of local Internet broadband access users	0.0136	
Development strategy (B)	Government planning (B1)	Policy emphasis	Number of times that AI-related keywords mentioned in the annual work report of local government	0.0357	0.1054
	Education planning (B2)	Subject construction in higher education	Number of AI related majors newly added in the undergraduate majors of local colleges registered or approved by the Ministry of Education	0.0697	
Development activities (C)	Business activities (C1)	the number of local AI enterprises	Number of enterprises in local AI industry	0.0599	0.4078
		the scale of local AI industry	Total asset scale of local AI industry	0.0845	
		the market share of local AI industry	Proportion of total main business income of local AI industry in the whole country	0.0799	
	Innovation activities (C2)	Research papers	Number of AI-related papers published/local population	0.0631	
		Patented inventions	Number of local AI-related patents/local population	0.1204	
Development quality (D)	Economic benefits (D1)	the profit of local AI industry	Total profit of local AI industry	0.0844	0.1892
	Robot application level (D2)	Industrial robots' application level	Total number of local industrial robots	0.0683	
	Production efficiency (D3)	TFP of AI industry	the TFP of AI industry calculated by the method of DEA-Malmquist	0.0364	

adopted to measure education planning. And it is measured by the number of AI related majors newly added to the undergraduate majors of local colleges registered or approved by the Ministry of Education of China every year, such as “Artificial Intelligence,” “Robotic Engineering,” “Intelligent Science and Technology,” “Intelligent Manufacturing Engineering,” etc.

Development activities reflect the prosperity of the local AI industry and the richness of local AI-related innovation achievements. This paper selects two secondary indices to explain development activities: business activities and innovation activities. First, business activities mainly reflect the prosperity of the local AI industry, including three tertiary indices, the number of local AI enterprises, the scale of the local AI industry, and the market share of the local AI industry in the country, respectively. Secondly, innovation activities mainly reflect the richness of local AI-relevant innovation outcomes, which are evaluated using two indices: research papers and patented inventions. Research papers and patents are often used to reflect the scientific and innovation activities [13,17,21]. Among them, research papers are measured by the number of locally published AI related papers (containing AI related keywords such as artificial intelligence, machine learning, image recognition, machine vision, intelligent robot, etc., in the title, keywords, or abstract) divided by local population. Similar to the research papers, patented inventions are measured by the number of local AI-related patents divided by the local population. The condition for patent retrieval is that the title or abstract contained AI-relevant keywords (the same as the keywords used in AI articles crawling), and the appearance patents are removed.

Development quality reflects the quality, benefit, and future potential of the local AIDEV. The development quality contains three indicators, namely, economic benefits, robot application level, and production efficiency, respectively. First, the economic benefit is evaluated based on the profits of the local AI industry. Subsequently, the industrial robot is a commonly used variable to measure AIDEV [5,25] which is measured by the number of local industrial robots. Following this, the production efficiency is measured by the total factor productivity (TFP) of the local AI industry, considering that TFP is widely used as a measure of technical progress and efficiency improvement over a certain period of time [53,54].

3.2. Data source

We use the sample period of 2011–2020 for the following reasons. From the perspective of Chinese AI development, the second decade of the 21st century is considered the beginning of the fourth wave of AI development [55]. Over the past decade, AI has been widely applied in various scenarios, such as search technology, data mining, machine learning, and natural language processing, and has entered people’s daily lives. Therefore, considering these factors, this article chooses 2011 to 2020 as the research period. The data we used in this study comes from the following sources.

First of all, the panel data of the AI industry in China, which are used to measure AI industry variables (the growth, the scale, the market share, the performance, and TFP calculation of the local AI industry), are obtained from the “China Information Industry Yearbook” and “China High Tech Industry Statistical Yearbook”. In addition, the number of local Internet broadband subscribers is collected from China Statistical Yearbook. Besides, the annual government work reports are obtained from the government websites. And the AI major data are obtained from the undergraduate professional filings and approval result documents published on the official website of the Ministry of Education of China. Moreover, the number of AI research papers is crawled from the China National Knowledge Infrastructure (CNKI). What’s more, the patent data are retrieved from the Incopat patent database. Furthermore, learning from Liu et al. [5] and Acemoglu and Restrepo [25], we calculate the numbers of industrial robots based on the data from the International Federation of Robotics (IFR) and China Labor Statistics Yearbook. The robot stock data provided by IFR are at the national industry level, and its industry classification standard is not consistent with that of China. Comparing the industry classification in IFR with the Industrial Classification for National Economic Activities (GB/T 4754–2017) of China, we match and sort out those industries that are common. Subsequently, we calculate the numbers of local industrial robots using Eq. (1). In the equation, the subscripts i, j, and t stand for the value of the variable of province i in j industry in year t, respectively. In this way, Rob_{jt} represents the national stock of industrial robots in industry j in year t, L_{ijt} is the number of employees in industry j in province i in year t and L_{jt} reflects the national number of employees in industry j in year t. The number of employees in provinces and industries are from the China Labor Statistics Yearbook.

$$\mathrm{Rob}_{it} = \sum_{j=1}^{J} Rob_{jt} \times \frac{L_{ijt}}{Ljt} \tag{1}$$

Next, to measure the TFP of the AI industry which is calculated using the DEA-Malmquist method, following Zhu et al. [56], Huang et al. [57], and Huang et al. [58], this paper uses capital stock and labor force as inputs, while the main business income is used as the outputs. Specifically, the data for investment in fixed assets of the AI industry is chosen to represent the capital stock and their price indices are collected from the National Bureau of Statistics of China. We use the perpetual inventory method according to Hall & Jones [59] and select 2011 as the base period for the calculation. Following this, the average number of employees in the AI industry is selected to measure the labor force. While main business income of the AI industry is converted into 2011 using the accumulated index of producer prices for industrial products which came from the National Bureau of Statistics of China. All the above data concentrate on 2011–2020, and we apply a linear interpolation method to supplement the small number of missing values.

4. Methodology

4.1. Entropy weight method

Based on the above evaluation system, we adopt the entropy weight method (EWM) to calculate the weight of each indicator and the AIDEV score for each province. The EWM, originally developed by Shannon & Weaver [60], is an objective evaluation method and widely applied to objectively measure the importance of each index [61]. It determines the weight of an index according to the discrete feature of the data, which avoids the interference of human factors [62]. The specific calculation process is as follows. Assuming that there are m indicators and n samples, and the j_{th} indicator for the i_{th} sample can be represented by a_{ij}.

The first step is standardization. All the indicators in this paper are positive indicators. Therefore, the standardization calculation method for a_{ij} is based on Eq. (2). The second step is to calculate the information entropy of each index. H_i stands for the entropy of the i_{th} index and it is measured by Eq. (3). After that, in Eq. (4), we calculate the weight of each index based on the information entropy and the weight is represented by $w_{i.}$ Finally, we calculate the score of each evaluation object based on the standardized value r_{ij} and weight w_i in Eq. (5).

$$r_{ij} = \frac{\alpha_{ij} - min\{a_j\}}{max\{a_j\} - min\{a_j\}} \tag{2}$$

$$H_i = -\frac{\sum_{j=1}^{n} r_{ij} \bullet \ln r_{ij}}{\ln n} \tag{3}$$

$$\omega_i = \frac{1 - H_i}{\sum_{i=1}^{m} 1 - H_i} \tag{4}$$

$$F_i = \sum_{i=1}^{m} \omega_i \bullet r_{ij} \tag{5}$$

4.2. Standard deviation ellipse

The Standard deviation ellipse (SDE) is widely used to reveal the spatial distribution characteristics and evolutionary process of the research objects [63,64]. We use the ArcGIS software to apply the SDE method in this paper. The SDE is composed of the mean center, azimuth, long half-axis, and short half-axis [65], which broadly indicate the center of gravity, relative position, main trend direction, main distribution direction and dispersion degree of AIDEV in China, respectively. And they are calculated by Eqs. (6)–(9). Specifically, $(\overline{X}, \overline{Y})$ is the weighted mean center; W_i is the spatial weight; (x_i, y_i) denotes the center coordinates of the *i-th* element; tan θ is the azimuth; σ_x and σ_y are the standard deviation for the long half-axis and short half-axis, respectively.

$$\overline{X} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \overline{Y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{6}$$

$$tan\ \theta = \frac{\sqrt{\left(\sum_{i+1}^{n} w_i^2 \widetilde{x}_i^2 - \sum_{i+1}^{n} w_i^2 \widetilde{y}_i^2\right)^2 + 4\sum_{i+1}^{n} w_i^2 \widetilde{x}_i^2 \widetilde{y}_i^2}}{2\sum_{i+1}^{n} w_i^2 \widetilde{x}_i^2 \widetilde{y}_i^2} + \frac{\sum_{i+1}^{n} w_i^2 \widetilde{x}_i^2 - \sum_{i+1}^{n} w_i^2 \widetilde{y}_i^2}{2\sum_{i+1}^{n} w_i^2 \widetilde{x}_i^2 \widetilde{y}_i^2} \tag{7}$$

$$\sigma_x = \sqrt{\frac{\left(\sum_{i=1}^{n} w_i \widetilde{x}_i \cos\theta - \sum_{i=1}^{n} w_i \widetilde{y}_i \sin\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{8}$$

$$\sigma_x = \sqrt{\frac{\left(\sum_{i=1}^{n} w_i \widetilde{x}_i \sin\theta - \sum_{i=1}^{n} w_i \widetilde{x}_i \cos\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{9}$$

4.3. Moran index

Spatial autocorrelation analysis is a quantitative description of the degree of correlation between different regions. We select the most frequently used measurement method, the global Moran index [66] and the local Moran index [67] to calculate the spatial autocorrelation of provincial AIDEV. The equations for global Moran's I and local Moran's I are as follows.

In Eqs. (10) and (11), n is the total number of samples; z_i and z_j refer to the specific value of the neighboring provinces i and j, respectively; ω_{ij} represents the spatial weight between provinces i and j. The spatial weight matrix we used is calculated by combining the geographical distance and the per capita GDP gap. The principle is that the smaller the geographical distance and the closer the economic level between two provinces is, the stronger the mutual influence, that is, the greater the weight.

$$Global\ Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(z_j - \overline{z}z_i - \overline{z}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}\left(z_i - \overline{z}\right)^2} \tag{10}$$

$$Local\ Moran's\ I = \frac{n(z_i - \overline{z})\sum_{j=1}^{n}\omega_{ij}\left(z_j - \overline{z}\right)}{\sum_{i=1}^{n}\left(z_i - \overline{z}\right)^2} \tag{11}$$

4.4. Dagum Gini coefficient and decomposition method

To quantitatively measure the degree of the spatial differences in AIDEV among regions in China, we follow Huang et al. [68] to adopt the Dagum Gini coefficient and its subgroup decomposition method. In this method, Dagum [69] decomposes the overall Dagum Gini coefficient (G) into three parts: intra-regional difference (G_w), inter-regional difference (G_{nb}), and intensity of transvariation (G_t), which meet the conditional of $G = G_w + G_{nb} + G_t$. The overall Dagum Gini coefficient is calculated by Eq. (12).

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|x_{ij} - x_{hr}\right|}{2n^2\overline{x}} \tag{12}$$

where n denotes the number of all provinces, k is the number of regions, i and r are subscripts for different provinces, x_{ji} (x_{hr}) represents the AIDEV value of the j (r) province in the i (m) region. And then, in Eqs. (13)–(18), G_{jj}, G_w, G_{jh}, G_{nb}, and G_t represent the Gini coefficient of j region, the internal difference of j region, the coefficient of variation between j region and h region, the difference between regions j and h and the intensity of the transfer variation, respectively.

$$G_{jj} = \frac{\frac{1}{2\overline{x}_j}\sum_{i=1}^{n_j}\sum_{j=1}^{n_j}\left|x_{ji} - x_{jr}\right|}{n_j^2} \tag{13}$$

$$G_w = \sum_{j=1}^{k} G_{jj}p_j s_j \tag{14}$$

$$G_{jn} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_k}\left|x_{ji} - x_{hr}\right|}{n_j n_h\left(\overline{x}_j + \overline{x}_h\right)} \tag{15}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_h\right)D_{ih} \tag{16}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_h\right)D_{ih} \tag{17}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_h\right)\left(1 - D_{ih}\right) \tag{18}$$

where d_{jh} represents the mathematical expectation of the AIDEV cumulative summation satisfying $x_{ji} > x_{hr}$ in region j and region h; p_{jh} denotes the mathematical expectation of the AIDEV cumulative sum satisfying $x_{ji} < x_{hr}$ in region j and region h, and F_j (F_h) denotes the cumulative distribution functions of AIDEV in the adjusted region j (h).

4.5. Kernel density estimation

By observing the characteristics of density curves, the kernel density estimation (KDE) method can help to discover the overall distribution and dynamic evolution patterns of the samples [68]. To further study the dynamic distribution of AIDEV in China, we also deploy the Kernel density estimation (KDE) method. Specifically, following Parzen [70], the kernel density curve is generated using Eq. (19):

$$f(x) = \frac{1}{NH}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{19}$$

where *k (x)* represents the kernel density function, N represents the number of observations, H stands for the bandwidth, X_i represents independent, identically distributed observations and x is the mean value of the observation. As shown in Eq. (20), the Gaussian Kernel function is deployed to estimate the kernel function.

$$K(x) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{x^2}{2}\right) \tag{20}$$

4.6. Gray prediction GM (1, 1) model

The gray prediction GM (1, 1) model is valid for forecasting time-series data with incomplete and limited sample sizes [64,71,72]. Therefore, considering that the research period of each province is only 10 years and there are huge differences between each province, the gray prediction GM (1, 1) model is used to separately forecast the future changing trend of the AIDEV for each province in China. The accuracy test level standard for the model is shown in Table 2. Further, this study also evaluated the forecasting performance by calculating the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) between the actual and predicted value [73–75], as shown in Eqs. (21)–(23).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\widehat{y}_i - y_i| \tag{21}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\widehat{y}_i - y_i}{y_i}\right| * 100 \tag{22}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\widehat{y}_i - y_i)^2}{n}} \tag{23}$$

4.7. Markov chain

Markov chain methods have been widely used to describe the dynamic evolution process of specific regional elements and phenomena [76,77]. To further reveal the characteristics of the spatial and temporal change process and patterns of AIDEV, this study introduces the traditional Markov chain and spatial Markov chain methods.

4.7.1. Traditional Markov chain

The traditional Markov chain follows the theory that the state at a future time point $t+1$ only depends on its current state distribution at time t and is not affected by the time before time t [78,79]. Thus, the change pattern of the event is evaluated by formulating a corresponding state transition probability matrix. The transition probability matrices are listed in Table 3, where m_{ij} is the probability of a province that transferring from state i in year t to state j in year $t+1$.

4.7.2. Spatial Markov chain

The spatial Markov chain can reveal the interactions between provinces by introducing the concept of spatial lag into the traditional Markov chain [78,79]. After adding a spatial factor, the matrix in the spatial Markov chain changes into an $N \times N \times N$ conditional transfer matrix. In this case, $m_{ij(k)}$ in the matrix stands for the probability that a province in state i at time point t transfers to state j at $t+1$ time point where the province is surrounded by state k provinces at the start.

5. Results and analysis

5.1. Analysis on spatiotemporal characteristics of AIDEV in China

5.1.1. General characteristics

As a commonly used objective weighting method [80,81], this study uses the entropy weight method to calculate the weight of each indicator in the indicator system. The weight of each indicator is shown in Table 1. By combining the evaluation system, provincial panel data of China’s 31 provinces, and indicator weights, we calculate the provincial AIDEV of China from 2011 to 2020. As shown in

Table 2
Gray prediction accuracy test level standard.

Accuracy	P	C
excellent	$0.95 \leq P$	$C \leq 0.35$
good	$0.80 \leq P < 0.95$	$0.80 < C \leq 0.50$
qualified	$0.70 \leq P < 0.80$	$0.5 < C \leq 0.65$
failed	$P < 0.70$	$1.65 < C$

Table 3
Traditional Markov transition probability matrix.

t/t+1	1	2	3	4
1	m_{11}	m_{12}	m_{13}	m_{14}
2	m_{21}	m_{22}	m_{23}	m_{24}
3	m_{31}	m_{32}	m_{33}	m_{34}
4	m_{41}	m_{42}	m_{42}	m_{44}

Table 1, among the primary indices, the weights of the development foundation, development strategy, development activities, and development quality reach 0.2976, 0.1054, 0.4078, and 0.1892 respectively, indicating that the development activities index is the primary index for improving the AIDEV, while the development foundation also has a significant impact on AIDEV. However, as a representative of future development potential and planning, development strategies and development quality must be improved. In terms of the tertiary index, the weights of the patented inventions, information infrastructure, the scale of local AI enterprises, the performance of local AI enterprises, and the market share of local AI enterprises are the top five among all the tertiary indices. These results reflect that the local AI ecosystem is crucial for improving AIDEV, and technological innovation is the driving force and source for promoting the high-quality and rapid development of AIDEV. These two factors would be the strategic policy focuses for promoting AIDEV.

Based on the provincial AIDEV in China, we calculate the average value of eight regions[1] and the whole country. First, from the overall development trend, as shown in Fig. 2, between 2011 and 2020 the national average of AIDEV in China has maintained growth over the years. This demonstrates that with the increasing maturity of AI technology and improved integration with physical industries, as well as the continuous improvement of related policies and regulations, China's AIDEV has shown a positive development trend over the past decade. This is consistent with the findings of other studies [14].

Second, from the development speed, the national average of AIDEV grew steadily from 0.0422 in 2011 to 0.0729 in 2016, with an average annual growth rate of 11.55 %. While during 2016 and 2018, it grew from 0.0729 to 0.1233, suggesting that the average annual growth rate highly increased to 30.05 %. But after two years of rapid growth from 2018 to 2020, it increased from 0.1233 to 0.1403, indicating the growth rate decreased to 6.67 %. In general, the development speed of AIDEV in China has gone through a trend of "steady increase to fast growth to slow rise."

The above results can be explained by the following events. In 2016–2018, Google's AI program AlphaGo defeated South Korean Go master Lee Se-dol and China's State Council issued the "New Generation Artificial Intelligence Development Plan," which raised the priority of the development of AI to the national strategic level [5]. These events played important roles in promoting AIDEV growth. However, in the next few years, the negative impact of factors such as Sino-US trade conflicts and the COVID-19 pandemic on the economy [82,83] also may hindered the rapid development of AIDEV in China. In the post-COVID-19 era, the government should continue to strongly support AI industry and AI technology innovation to realize AIDEV and leverage the important role of AI in comprehensively supporting the resumption of production as well as the development of the digital economy.

Third, as shown in Fig. 2, it can be observed that there is a significant disparity in the development of AIDEV across different regions in China. The AIDEV in the Eastern coast, Southern coast, and Northern coast are much higher than the national average, exhibiting a spatial distribution pattern of gradually weakening from east to west and south to north. Large regional differences are detrimental to the AIDEV. To intuitively reveal the spatial distribution of AIDEV in China, the AIDEV of each province in 2011, 2014, 2017, and 2020 are selected for visual analysis using ArcGIS software (Fig. 3). Specifically, among the 31 provinces, the AIDEV of Beijing, Guangdong, Jiangsu, Zhejiang, and Shanghai, which are mainly located in coastal areas, remained among the top five provinces from 2011 to 2020. While the AIDEV of provinces such as Xinjiang, Tibet, Qinghai, Inner Mongolia, and Guizhou which are mainly located in the Southwest, Northwest, and Middle Yellow River, are significantly lower than those of the coastal provinces. From the perspective of development speed, the Middle Yangtze River, Northwest, Middle Yellow River, and Southwest have the top 4 average annual growth rates among eight regions.

In conclusion, the AIDEV in China presented a gradient distribution pattern, which is "eastern > central > western". Some studies also support this viewpoint [33], this is mainly because of the sound economic foundation and advanced science and technology in eastern and coastal areas of China, leading to a significant first-mover advantage of AIDEV. Meanwhile, some inland areas (e.g., the

[1] The division method of the 8 major economic regions used in this paper was proposed by the Ministry of Development Strategy and Regional Economic Research in the Development Research Center of the State Council of China.

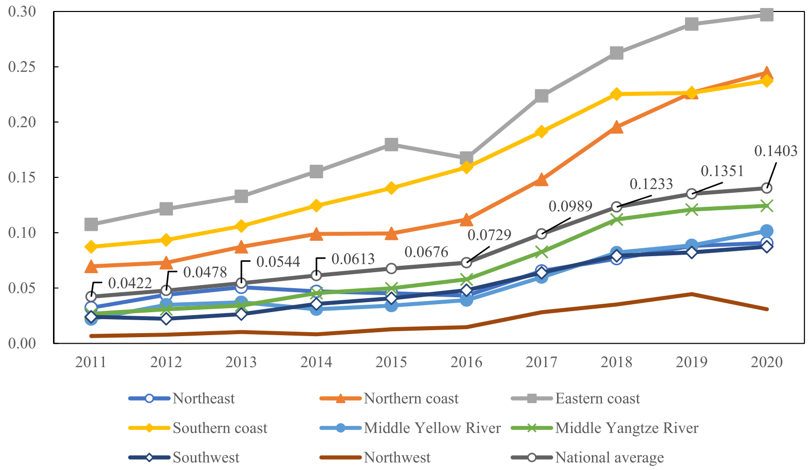

Fig. 2. Aidev of China from 2011 to 2020.

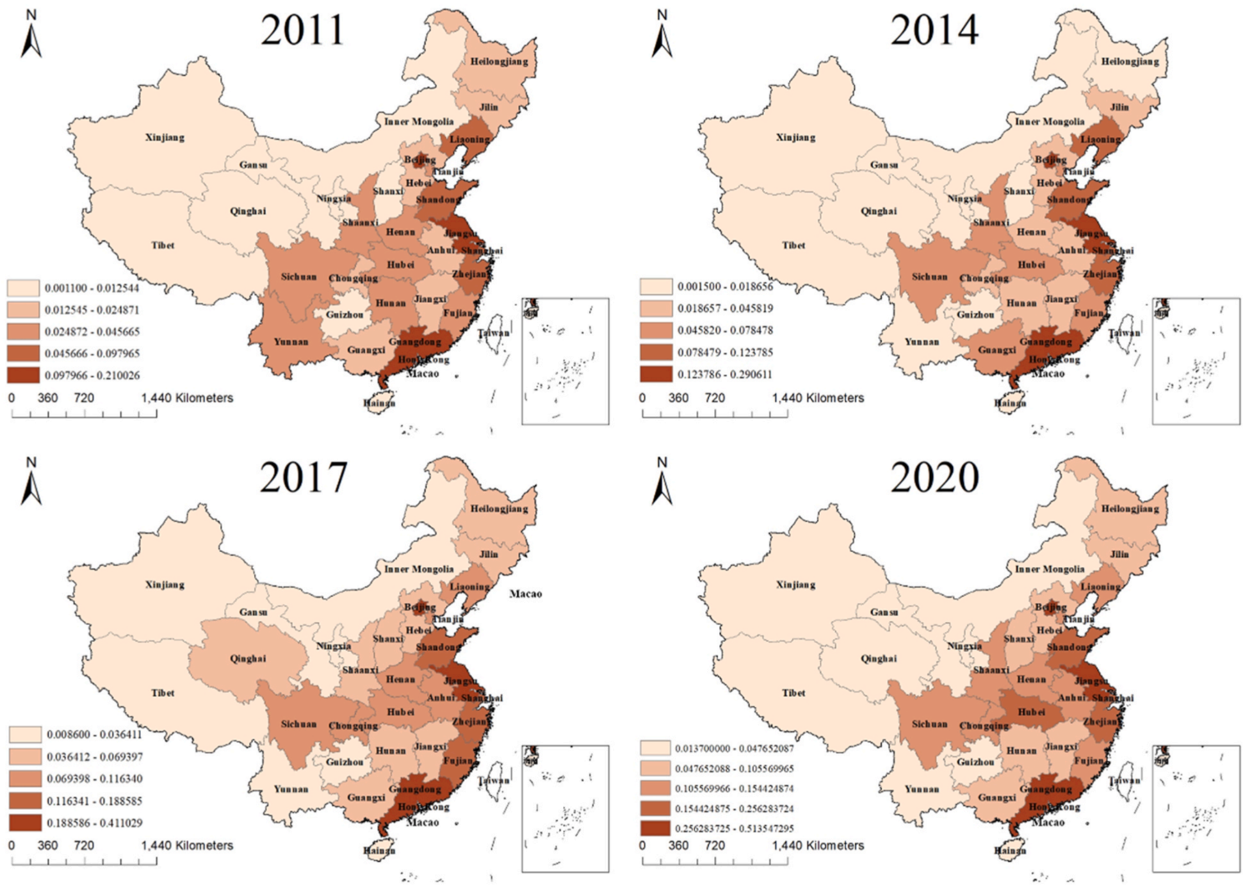

Fig. 3. Characteristics and patterns of spatial differences in AIDEV of China.
Notes: The darker areas in Fig. 3 indicate higher AISD levels.

Middle Yangtze River, Northwest, Middle Yellow River, and Southwest) are catching up to the AI developed regions, showing a remarkable average annual growth rate. This shows that although the development of AI in inland areas starts late, it also develops rapidly with support from the government, which offers the prospect of long-term and balanced development of AI throughout the country.

5.1.2. Change in the center of gravity

Considering 2011 and 2020 as representative years, we use the standard deviation ellipse model to measure the center of gravity of the AIDEV and combine it with the ArcGIS software's spatial statistics tool to visualize its trajectory. According to Table 4 and Fig. 4, within the research scope, the center of gravity of the ellipse is located in the Henan Province and it moves from (115.44° E, 32.88° N) to (114.92° E, 33.22° N) at a distance of 60.36 km, shifting westward by 0.29° and northward by 1.22°, reflecting the reduction in the gaps between the AIDEV in the northwest and southeast of the country. Meanwhile, the center of gravity of the ellipse is closely aligned with the average gravity of the center of the GDP calculated by Duman [63]. This also serves to some extent as evidence that the major AI industry activities are concentrated in economically developed regions. In addition, the scope of the resilience of AIDEV in China is reduced, showing a trend of space contraction for AIDEV in China. At the same time, the long half-axis of the AIDEV in China increased from 711.8862 km in 2011 to 735.2695 km in 2020, and the short semi-axis shortened from 1055.0767 km to 1009.5001 km, indicating the clear northeast-southwest direction of clustering characteristics of AIDEV in China. Overall, the standard deviation ellipse of AIDEV once again proves the northeast–southwest spatial pattern in China and the rise of AIDEV in the western and northern areas, which causes the movement of the center of gravity.

5.2. Analysis on regional differences and sources of AIDEV in China

The above analyses reveal an unbalanced spatial distribution of AIDEV in China. To further explore the size and source of the regional differences of the AIDEV in China, we divided China into eight regions and used the method of Dagum Gini coefficient calculation and subgroup decomposition to measure the overall, intra-regional, and inter-regional differences in the AIDEV of China quantitatively.

5.2.1. Overall regional difference

Fig. 5 presents the Dagum Gini coefficient of AIDEV in China from 2011 to 2020. In terms of the overall trend, the overall Dagum Gini coefficient of AIDEV fluctuated between 0.5113 and 0.5411 in the first four years, and then it showed a continuous decline from 0.5138 to 0.4377 in the next five years, indicating a decrease in regional differences. The maximum and minimum overall regional differences of AIDEV appeared in 2012 and 2019, at 0.5411 and 0.4377, respectively. In terms of the different sources of differences, the trend of the inter-regional differences, which is the largest among the three types of differences, also shows a gradual decline, and its change trajectory is similar to that of the overall differences. Subsequently, the intra-regional and intensity of transvariation differences are relatively very low and stable, with averages of 0.0347 and 0.0858, respectively. Hence, we can draw a conclusion that in 2011–2020, the AIDEV in China has obvious variations between regions, which is consistent with the results from some research reports [84]. Meanwhile, the spatial differences of AIDEV have narrowed and inter-regional differences remain the major source of regional differences in AIDEV. Happens to hold the same view as Lv & Hao [85]. For this reason, it is necessary for authorities to develop relevant policies to narrow the regional differences and stimulate the AIDEV in the future.

5.2.2. Intra-regional difference

Fig. 6 shows the evolution of the intra-regional differences in AIDEV in China. From the perspective of intra-regional comparison, the Southern coast (an average of 0.4714) is highest, followed by the Northern coast (0.3508). The reason is that, in the Southern coast area, there is a large gap between Guangdong, whose AIDEV is leading in China (1st in 2011–2019), and Hainan (around 26th) and Fujian (around 8th). The situation in the northern coastal areas is roughly similar (the gap between Beijing and Hebei). From the perspective of evolutionary trends, the intra-regional differences in Eastern coast and Southern coast generally show a downward trend indicating that the imbalance in these areas gradually decreases, while the intra-regional difference in Northern coast is relatively smooth and fluctuates around 0.35. In conclusion, the regions with large intra-differences are those regions that include provinces with outstanding AIDEV. The intra-differences fluctuate significantly in many regions. Achieving coordinated development within a region is a prerequisite for achieving greater coordinated development among regions. Therefore, the government needs to focus on policies to strengthen cooperation and promote the common development of the AI industry among neighboring provinces within the same region.

5.2.3. Inter-regional difference

Fig. 7 shows the characteristic of the inter-regional differences in the AIDEV of China. From the perspective of average value, during the research period, the average value of the inter-regional differences of AIDEV is 0.5031 and they generally have been declining as a whole. And the regional difference between the Eastern coast and Northwest is the largest, with a mean value of 0.8310, and the regional difference between the Middle Yellow River and Middle Yangtze River is the smallest, with a mean value of 0.2763. The inter-regional differences between coastal areas (Eastern coast and Southern coast, excluding the Northern coast) and inland areas are larger than the average because of the high level of AIDEV in the Eastern coast and Southern coast. Therefore, the government needs to pay

Table 4
Standard deviation ellipse-related parameters of the AIDEV in China.

Year	Center Coordinates (°)	Long semi-axis (km)	Short semi-axis (km)	Shape area (km^2)	Azimuth (°)
2011	115.15° E, 32.32°N	711.8862	1055.0767	2359484.1495	15.7690
2020	114.46°E, 33.54°N	735.2695	1009.5001	2331724.9349	18.2264

Fig. 4. Standard deviation ellipse of the AIDEV in China.

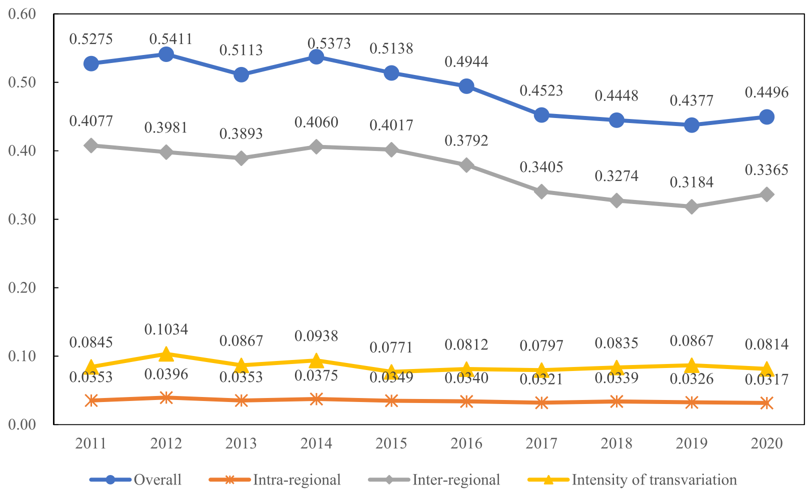

Fig. 5. The trends of Dagum Gini coefficient of AIDEV in China.

attention to the persistent regional imbalance and close the gap between the coastal area and other areas.

From the perspective of change pattern, the inter-regional differences between several regions show a decreasing trend, which can be summarized into two types. The first type of downward trend is owing to the gap between the AIDEV of the developed coastal area and the less-developed areas has narrowed. From the conclusion in 4.1, we know that several inland areas have higher growth rates

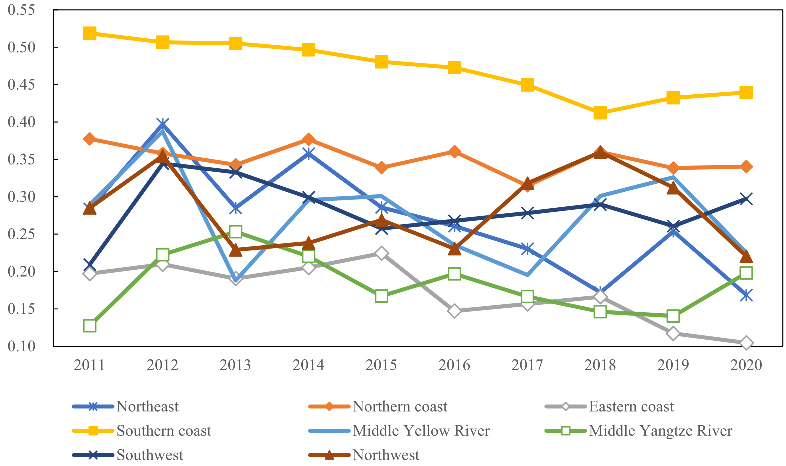

Fig. 6. The trends of intra-regional Dagum Gini coefficient of AIDEV in China.

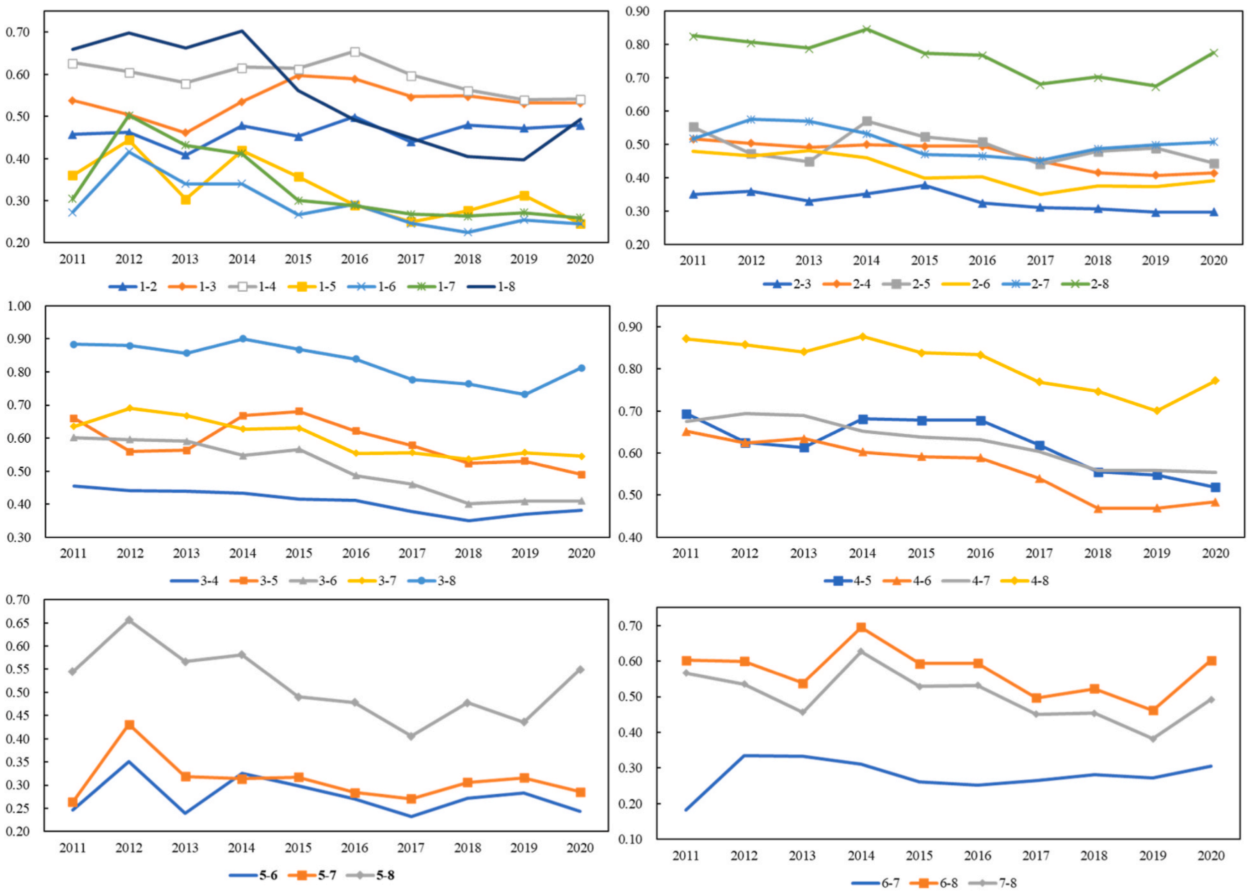

Fig. 7. The trends of inter-regional Dagum Gini coefficient of AIDEV in China.
Notes: 1, 2, 3, 4, 5, 6, 7, 8 represents the Northeast, Northern coast, Eastern coast, Southern coast, Middle Yellow River, Middle Yangtze River, Southwest and Northwest in China. For example, '1–2' stands for the inter-regional Dagum Gini coefficient between Northeast and Northern coast. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

than the coastal areas. Therefore, inter-regional differences between some areas such as the Northern coast-Northwest, Eastern coast-Southwest, and Southern coast-Northwest are decreasing. Besides, the second type of gap narrowing occurs between geographically adjacent regions, such as, the Northern coast-Middle Yellow River, Eastern coast-Southern coast, Middle Yellow River-Northwest, and Southwest-Northwest. This phenomenon implies that the possible resource sharing and economic spillover effect, which rely on geographical advantages may effectively reduce the AIDEV gap between the adjacent regions. To explain this phenomenon, further analysis of spatial correlation and dynamic evolution will be made in the following chapters.

5.3. Analysis on spatial correlation of AIDEV in China

The above studies confirm that the AIDEV in China is spatially unbalanced and exhibits obvious variations between regions. However, there is still a lack of evidence to prove that the unbalanced state is randomly distributed. Hence, this study introduces the global spatial autocorrelation and local autocorrelation methods to analyze the spatial dependency and spatial clustering characteristics of AIDEV.

5.3.1. Global spatial autocorrelation test

Table 5 presents the global Moran's index and statistical test results for AIDEV in China. As observed from Table 5, the global Moran's index is positive in all the research years, and passes the significance test of 1 % except for the 5 % level significance in 2012, indicating that AIDEV in China has a significant spatial positive correlation. In other words, the AIDEV is affected by its adjacent provinces' AIDEV levels, presenting a clear spatial aggregation feature. In the aspect of annual change, the global Moran's indices are around 0.22 and change slightly, which implies that the spatial correlation between provinces has not increased significantly as well. Therefore, China's government should further promote the flow of resources, talents, and funds related to the AIDEV between the provinces.

5.3.2. Local spatial autocorrelation test

For further analyzing the spatial clustering characteristic, the local Moran's index is employed to identify the spatial agglomeration category and autocorrelation features of AIDEV in each province. Table 6 lists the results of the local spatial autocorrelation test for AIDEV in 2011 and 2020. There are four groups in Table 6. Specifically, the HH group stands for high value province surrounded by high value province, the LH group stands for low value province surrounded by high value province, the LL group stands for low value province surrounded by low value province, and the HL group stands for high value province surrounded by low value province. According to Table 6, we obtain some important findings.

First, most of the provinces are located in the HH and LL groups. In 2011 and 2020, there were a total of 27 and 23 provinces that fell into the above two groups, respectively, which proves that the state of agglomeration of China's AIDEV remains relatively stable with a characteristic of "high aggregation, low aggregation" and basically presents a spatial binary distribution characteristic. Specifically, the provinces in the HH group are mainly from coastal areas with high AIDEV and the provinces in the LL group are mainly from western or central areas. While for provinces in the LL quadrant, they generally have a low AIDEV and their contiguous provinces are similar with a low AIDEV, showing a low-low cluster, for example, Tibet and Jilin. Second, compared to 2011, only a few provinces changed their spatial agglomeration type in 2020, and none of the provinces changed to HH group where it may lead to multiple effects as "$1+1>2$" through resource reallocation. Therefore, it still needs great effort to achieve a balanced spatial distribution of AIDEV in China in the short time.

5.4. Analysis on dynamic evolution of the AIDEV in China

To further revealing the dynamic evolution and transfer trends of AIDEV in China, this paper deploys the kernel density estimation, gray prediction GM (1,1) model, and the Markov chain method.

5.4.1. Dynamic distribution

For studying the dynamic evolution characteristics of the AIDEV in China, Stata16 software is applied to use the kernel density

Table 5
Moran's I and its statistical test of AIDEV of provinces in China.

Year	I	E(I)	SD(I)	Z	*P*-value
2011	0.2068	−0.0333	0.0907	2.6481	0.0081
2012	0.2022	−0.0333	0.0928	2.5393	0.0111
2013	0.2219	−0.0333	0.0919	2.7762	0.0055
2014	0.2148	−0.0333	0.0918	2.7038	0.0069
2015	0.2145	−0.0333	0.0902	2.7476	0.0060
2016	0.2171	−0.0333	0.0895	2.7998	0.0051
2017	0.2310	−0.0333	0.0918	2.8789	0.0040
2018	0.2393	−0.0333	0.0933	2.9232	0.0035
2019	0.2532	−0.0333	0.0936	3.0615	0.0022
2020	0.2183	−0.0333	0.0932	2.6983	0.0070

Table 6
Province classification based on four agglomeration types.

Group	Provinces in 2011	Provinces in 2020
HH	Beijing, Shanghai, Jiangsu, Zhejiang, Fujian (5)	Beijing, Shanghai, Jiangsu, Zhejiang, Fujian (5)
LH	Tianjin (1)	Tianjin, Inner Mongolia, Chongqing (3)
LL	Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang (22)	Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hunan, Guangxi, Hainan, Guizhou, Yunnan, Tibet, Gansu, Qinghai, Ningxia, Xinjiang (18)
HL	Liaoning, Shandong, Guangdong (3)	Shandong, Hubei, Guangdong, Sichuan, Shaanxi (5)

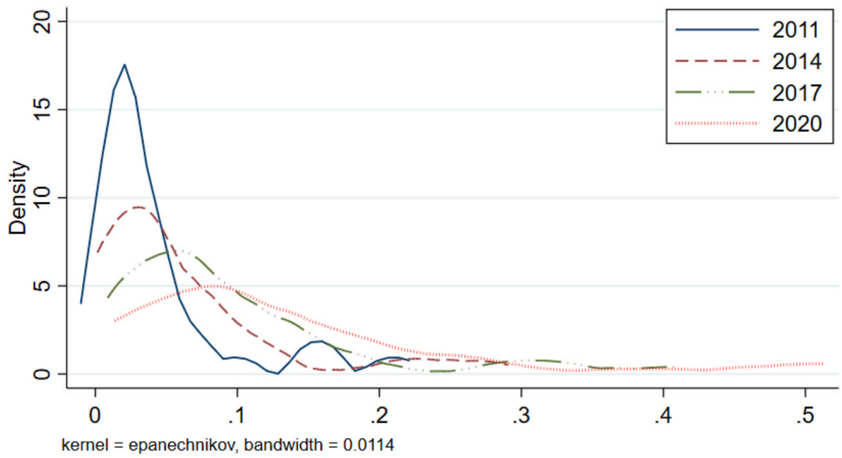

Fig. 8. Kernel density curve of AIDEV in China.

estimation method, and we consider 2011, 2014, 2017, and 2020 as the typical years to analyze the kernel density curves of the AIDEV, as shown in Fig. 8. With aspect to the change in position, from 2011 to 2020, the center of the curve gradually shifted to the right, suggesting that the AIDEV continuously improved over time. In respect of the shape of the curves, a significant right-hand tail can be clearly observed in the curve, indicating an increasing disparity between high-level provinces and other average-level provinces. However, on the other hand, during the sample investigation period, the height of the main peak of the curve decreases, the width of the main peak is getting wider, and the small peak continues to decrease and nearly disappears in 2020. In conclusion, these phenomena indicate that although AIDEV is still insufficient and uneven, the degree of concentration and polarization trend of AIDEV in China has been weakening, and the coordinated development of AIDEV in China is improving.

5.4.2. *Evolution trend*

In view of the time series data of AIDEV for China's 31 provinces from 2011 to 2020, this paper selects the GM (1.1) model to examine the actual and predicted values of AIDEV to reveal their evolution trends. During the accuracy test of the GM (1.1) model, 18 provinces meet the criteria of $P \geq 0.95$ and $C \leq 0.35$, 8 provinces satisfy the condition of $P \geq 0.8$ and $C \leq 0.5$, 4 provinces fulfill the term of $P \geq 0.7$ and $C \leq 0.65$, and Qinghai province fails to pass the error test. Therefore, the model is accurate and the data from the 30 provinces can be applied to make predictions. Table 7 shows the test value, accuracy of prediction, and prediction value of top ten

Table 7
Gray prediction error test and prediction result of top 10 provinces in AIDEV.

	Test value		Accuracy of prediction			Prediction value		
	C	P	MAE	RMSE	MAPE	2021	2022	2023
Beijing	0.1778	1	0.0204	0.0005	8.01 %	0.6145	0.7263	0.8583
Guangdong	0.1287	1	0.0097	0.0136	2.65 %	0.5941	0.6584	0.7296
Jiangsu	0.2990	1	0.0200	0.0251	6.98 %	0.4596	0.5058	0.5567
Zhejiang	0.1587	1	0.0087	0.0109	5.68 %	0.3224	0.3798	0.4476
Shanghai	0.2410	1	0.0091	0.0122	6.21 %	0.2752	0.3090	0.3469
Shandong	0.1413	1	0.0062	0.0083	4.36 %	0.2824	0.3314	0.3890
Hubei	0.1083	1	0.0049	0.0060	4.61 %	0.2503	0.2998	0.3591
Fujian	0.3373	0.9	0.0117	0.0154	11.13 %	0.2087	0.2395	0.2749
Sichuan	0.3252	0.9	0.0086	0.0126	15.15 %	0.1734	0.2050	0.2424
Shaanxi	0.3402	1	0.0121	0.0159	13.39 %	0.2049	0.2518	0.3093
National average	–	–	–	–	–	0.1762	0.2054	0.2399

provinces in AIDEV. As can be seen from Table 7, we also calculate the national average of the predicted value in 2021–2023. Overall, the prediction results show that the AIDEV of China is on a steady upward trend over the next three years, which could offer an important reference for the authorities' decision-making.

The gray prediction only reflects the overall evolution tendency of AIDEV in China. For further study, the traditional Markov transition probability matrix which is based on one-year lag is estimated to analyze the overall evolution pattern of AIDEV in China; the matrix is calculated using MATLAB software and the results are shown in Table 8. Specifically, the AIDEV values of China are divided into four states from low to high, based on the quantile division method (using 1/4, 1/2, and 3/4 quantiles as the boundaries), namely, I, II, III, IV. Besides, the entire sample investigation period is divided into two stages which are 2011–2015 and 2016–2020, in accordance with the evolutionary trend shown in Fig. 2.

As observed from the matrix in Table 8, whether in 2011–2015 or 2016–2020, the values on the main diagonal are bigger than those off the main diagonal, indicating that the probability of maintaining the original level is higher. Among the values on the main diagonal, the minimum value is 0.567. In other words, the probability of AIDEV in any year maintaining its original state in the next year is greater than 50 %, and an AIDEV in high level is the most stable. Besides, the AIDEV of some provinces also shift upward and downward. During the period 2011–2015, more than 16 % of the provinces can transition to higher adjacent states, and this number increases to 33 % during the period 2016–2020.

In general, we can draw the following conclusions. First, the state of AIDEV is relatively stable. Provinces with lower AIDEV still face challenges in catching up with those at higher levels. Second, the state transfer of AIDEV usually occurs within adjacent states, among which the probability of transfer from I to II is the highest. And it is hard for provinces to realize leapfrog development in the near future. Third, in terms of time, the AIDEV became more active and made it easier to achieve upward development in 2016–2020.

For deeper investigating the long-term transfer trend and spatial interaction impact on the AIDEV in China and whether the AIDEV gap between adjacent provinces will be effectively reduced owing to geographical advantages, this paper establishes the spatial Markov transition probability matrix of AIDEV in China (Table 9). Through the results in spatial Markov transition probability matrix, we could draw a conclusion that geography plays a crucial role in the process of state transition and the AIDEV in China has a spatial spillover effect. First, the AIDEV of surrounding provinces influence the probability of provinces to maintain provinces' original development level, which promotes the formation of the "club convergence" phenomenon. For example, the probabilities of I level provinces maintaining their original state in the traditional Markov transition matrix are 0.686 and 0.667, respectively, as shown in Table 9. However, when they are surrounded by I or II level, the probabilities increase to 0.792 and 0.744, respectively.

Second, the provinces with a high level of AI development would probably boost the neighboring provinces to transfer upward while low AIDEV neighborhoods would hinder the increase in AIDEV of the province. For instance, the probability of II level province developing into III level is 0.200 or 0.333 in the traditional Markov transition probability matrix. However, if it is surrounded by III level provinces, the probability increases to 0.367. This may be attributed to the fact that the talent, capital, and technology advantages of high-AIDEV provinces not only improve the local AIDEV, but also optimize the AI industrial structure, improve the AIDEV of surrounding provinces, and narrow the gap between provinces. This finding is in line with previous studies questioning whether the radiation effect brought by geographic context can promote common progress among adjacent regions [76]. Therefore, it is critical to consider how to promote spatial spillover effects in AIDEV-leading regions and enhance the acceptance capacity of underdeveloped AIDEV regions.

6. Conclusions and discussion

6.1. Conclusions

Based on a literature review, this study establishes an evaluation system and measures China's provincial AIDEV from 2011 to 2020. Subsequently, we further analyze the general characteristics, regional disparity, spatial correlation, and dynamic evolution of the AIDEV in China. The main research conclusions are as follows:

(1) Among the evaluation indices reflecting the AIDEV, the development activities (C) are the main stimuli in improving AIDEV, indicating that the local AI industry is the main body to improve AIDEV. In particularly, innovation is the driving force behind AIDEV. The development quality and planning, which represent the potential and planning for future long-term development, need to be improved. (2) The AIDEV of the national average and all regions exhibited an upward trend. Specifically, 2016 to 2018 was the fastest-growing stage of AIDEV in China. Meanwhile, the AIDEV in China shows an obvious unbalance in the spatial distribution of "eastern > central > western". The good news is that some inland provinces with relatively underdeveloped AIDEV have higher growth rates and are catching up with developed provinces. (3) The overall and inter-regional differences in the AIDEV of China are decreasing and the

Table 8
Traditional Markov transition probability matrix of AIDEV in China.

—	2011–2015				—	2016–2020			
	I	II	III	IV		I	II	III	IV
I	0.686	0.314	0.000	0.000	I	0.667	0.333	0.000	0.000
II	0.200	0.567	0.200	0.033	II	0.091	0.576	0.333	0.000
III	0.000	0.067	0.767	0.167	III	0.000	0.034	0.621	0.345
IV	0.000	0.000	0.034	0.966	IV	0.000	0.000	0.103	0.897

Table 9
Spatial Markov transition probability matrix of AIDEV in China.

Spatial Lag	T/(T+1)	T = 1			
		I	II	III	IV
I	I	0.792	0.167	0.042	0.000
	II	0.667	0.333	0.000	0.000
	III	0.000	1.000	0.000	0.000
	IV	0.000	0.000	0.000	0.000
II	I	0.744	0.233	0.023	0.000
	II	0.088	0.676	0.235	0.000
	III	0.000	0.167	0.833	0.000
	IV	0.000	0.000	0.000	1.000
III	I	0.667	0.333	0.000	0.000
	II	0.067	0.567	0.367	0.000
	III	0.000	0.043	0.761	0.196
	IV	0.000	0.000	0.000	1.000
IV	I	0.000	0.000	0.000	0.000
	II	0.000	1.000	0.000	0.000
	III	0.000	0.000	0.500	0.500
	IV	0.000	0.000	0.000	1.000

inter-regional differences are the major differences resource. The narrowing trend of inter-regional differences often occurs in two situations: the first type is within the AIDEV of the developed coastal area and the less developed area, and the second type is within adjacent regions. (4) For global spatial autocorrelation, there is a significantly positive spatial autocorrelation, which indicates that AIDEV in a certain province is affected by its adjacent provinces. For local spatial autocorrelation, most of the provinces are showing high-high agglomeration and low-low agglomeration features. Besides, only a few provinces have changed their spatial agglomeration type, indicating that it will be hard to achieve a balanced spatial distribution of AIDEV in China in the near future. (5) The concentration and polarization phenomenon of AIDEV in China have weakened. On this basis, the prediction results reflect a continued improvement in the national average of AIDEV in China from 2021 to 2023. In the view of evolution pattern, we could find a club convergence phenomenon in the AIDEV of China. In addition, the state transfer in the AIDEV of China often occurs at adjacent levels. Meanwhile, the spatial factor would affect the probability of province to transfer. High AIDEV provinces will increase the probability of the surrounding provinces' AIDEV to transfer upward.

6.2. Theoretical implications

Our findings make the following theoretical contributions.

(1) This study expands the research perspective in the field of AI research. On the one hand, most studies focus on the role of AI on social and economic issues [20]. This article proposes the concept of AIDEV and provides a specific definition that emphasizes the long-term and healthy development of AI technology and industry and expands the research stream in the AI field. On the other hand, most of the previous research reports on AI mainly focus on the country level [11,13] or enterprise level [23,24], making the provincial level research a kind of "black box." Therefore, we measure the provincial AIDEV of China from 2011 to 2020, which provides an innovative perspective for the research on AI development.

(2) This paper enriches the research results in the field of AIDEV measurements. Prior studies and reports mostly used only a single proxy variable to measure AI [26] or remained in a period of describing each aspect of AI development, lacking the quantitative measurement of AIDEV [12]. Through a literature review and based on IE theory, we construct a valuable conceptual framework and develop a scientific evaluation system which breaks through the past studies that merely focused on the current development results or activities while neglecting the future-oriented long-term development quality and strategy [21,22]. This scientific evaluation system is not only applicable to measuring AIDEV in China, but can also be used to evaluate AIDEV in other areas or adapted to measure the development level of other advanced technologies. For research focusing on the impact of AI on socioeconomic phenomenon, this evaluation system could offer important insights into how to measure AIDEV precisely.

(3) This study contributes to the IE theory by expanding its application scenarios and research topics. The literature review shows that the AIDEV measurement, which constructs an evaluation system based on scientific theory, is rather limited [17]. And prior IE theory research was mainly used in the field of innovation management (e.g., Xie & Wang [30]). Considering the regional AIDEV as an IE and developing an evaluation framework based on the four-quadrant division method could improve the scientificity and comprehensiveness of the AIDEV measurements. Therefore, we creatively break through the research gap in most of the previous studies' lack of theoretical support to measure AI [17,21] and extend our understanding of how IE theory can be used in this new research topic.

6.3. Policy recommendations

The practical implications of this study primarily revolve around how policymakers can promote the long-term development of

AIDEV based on our empirical results, and can be summarized as follows.

(1) In the "Development Plan for the New Generation of Artificial Intelligence" released by the State Council, it is highlighted that it is crucial to seize the important historical opportunity of AI development. Following this, our analysis shows that although the overall AIDEV has improved, the development of AIDEV has slowed down in the last two years. Therefore, it is necessary for the Chinese governments to continue to prioritize and increase its policy support for AIDEV. First, the steps to take should focus on those indicators with high weights in the evaluation system. Our index weight results indicate that the AI industry is the main body for improving AIDEV and the weight of patented inventions is the highest. Therefore, the authorities should improve their industrial policies and enhance the industrial competitiveness of the AI industry. Similarly, technical innovation is a critical factor in AIDEV. Hence, policies should encourage patent application and promote patent development. Second, to achieve the persistent and high-quality development of AI technology and industry, both central and local governments need to attach importance to the formulation of future strategies, including AI education, AI application, and talent cultivation.
(2) Local government should develop differentiated AIDEV strategies based on local conditions. The empirical results of this study indicate significant variations in AIDEV levels across different regions of China. Regarding the eastern and coastal area of China, which have a sound economic foundation and are leading in terms of AIDEV levels, should make use of their basic advantages and leading role in promoting the widespread application of AI in various industries, thereby achieving industrial upgrading and value innovation. For example, A Province in the southern of China proposed leveraging local AI supercomputing platforms and the technical support from universities such as the Chinese Academy of Sciences to create advantageous and distinctive AI industry clusters. While provinces with low AIDEV levels, which are primarily in western or central China, empirical results indicate that although their development is still in a backward state, they have shown a higher growth rate in recent years, resulting in a catching-up effect. Therefore, breakthrough development can be achieved by promoting the AI industry in a certain subdivision field with local characteristics. For example, in B Province which is in the northern of China, by taking the lead in local AI companies, and combining the foundation of industrial development and practical needs in B province, a distinctive AI industry system with provincial characteristics is being constructed.
(3) The results on spatial correlation and evolutionary trends indicate a positive spatial correlation and spatial spillover effect in China's AIDEV. Therefore, the central government should use the spatial effect of AIDEV, promote regional cooperation and experience exchange, and motivate the AI-developed areas to bring along the less developed areas. Specifically, the central government should encourage the western and central areas to actively learn and use the experience that comes from AI developed area and reasonably undertake the transfer of the AI industry to realize the leapfrog development of AIDEV (e.g., C Province in the western of China has greatly improved the development of the local AI industry through cooperation with leading AI enterprises such as iFLYTEK in recent years). During this process, to break barriers and promote the full flow of AI relevant capital, technology, talents, and other production factors and resources between provinces, authorities should build more innovative communication platforms and expand the openness of the AI industry, and promote regional cooperation. For example, the Artificial Intelligence Innovation Center of D province in the western of China, in collaboration with computing facilities in its adjacent provinces, has achieved cross-regional cooperation in computing power. This enables the efficient interconnection and scheduling of high-performance computing power in the western regions.
(4) The analysis of the regional differences and dynamic evolution of AIDEV shows that although regional disparities and polarization in China's AIDEV have been alleviated, there still exists a significant disparity in AIDEV between high-level and low-level areas, and it is difficult for low-level areas to catch up in a short period of time. Therefore, in order to keep track of the dynamics of AI development and enhance government attention, the government should establish an advanced technology long-term development evaluation system and incorporate it into the government departments' performance assessment mechanisms. Considering AI as an example, the scientific measurement of AIDEV is the premise for the government to take targeted measures to promote AIDEV. To achieve this, in the first place, the authority needs to formulate more accurate and standardized AI industry definitions and AIDEV standards, and establish a systematic AI basic database. After that, provinces should develop a multidimensional AIDEV evaluation index system with local characteristics and regularly track the technological development. For example, in the "New Generation Artificial Intelligence Development Action Plan (2019–2023)" of S city in the southern of China, it is proposed to establish an AI industry tracking research platform, an AI industry statistical indicator system, and a statistical system to strengthen industry monitoring, and provide decision-making support for policy adjustments. Moreover, AIDEV should be included in the government achievement assessments to encourage governments at all levels to consistently pay more attention to and vigorously support the long-term development of advanced technology.

6.4. Limitation and future discussion

The limitations and prospects of this paper mainly include two aspects: data acquisition and evolutionary mechanisms. In the data acquisition, on the one hand, there is no officially published AI industry data or yearbook in China. Therefore, because of the difficulty of city-level data acquisition, and because some statistical yearbooks have not been updated to the latest year, we cannot use the micro city-level data and update our data to the latest year. Therefore, future research could measure the AIDEV at the city level by issuing questionnaires to AI enterprises and using other methods to collect data to improve the accuracy and reliability of the results. Besides, this paper mainly focuses on the spatiotemporal distribution and dynamics evolution without analyzing the evolution mechanism of AIDEV. Follow-up research can compensate for this gap by using spatial econometric models to further explore the key drivers and evolution mechanisms of AIDEV.

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Data availability statement

Has data associated with your study been deposited into a publicly available repository?
No.
Has data associated with your study been deposited into a publicly available repository?
Data included in article/supp. Material/referenced in article.
Data will be made available on request.

CRediT authorship contribution statement

Yanming Sun: Supervision, Project administration, Funding acquisition, Conceptualization. **Zhaocong Wu:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation. **Jingni Lan:** Writing – original draft, Methodology, Conceptualization. **Yunjian Li:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Formal analysis, Conceptualization. **Zixin Dou:** Software, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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