Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Bridging or widening the divide? Exploring the role of AI technology in Smart City Development Efficiency and Spatial-temporal Divergence in China

Zhong Fang

fazhong02@fjnu.edu.cn

Fujian Normal University

Ying Chen

Fujian Normal University

Peiqi Shi

Fujian Normal University

Article

Keywords: Smart Divide, AI Technology, Smart City, Spatial-temporal Divergence

Posted Date: October 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11307016/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Bridging or widening the divide? Exploring the role of AI technology in Smart City Development Efficiency and Spatial-temporal Divergence in China

Zhong Fang
School of Economics, Fujian Normal University
Fuzhou, Fujian 350007, P.R. China
E-mail: fazhong02@fjnu.edu.cn
Ying Chen
School of Economics, Fujian Normal University
Fuzhou, Fujian 350007, P.R. China
E-mail: qbx20240006@yjs.fjnu.edu.cn
Peiqi Shi
School of Economics, Fujian Normal University
Fuzhou, Fujian 350007, P.R. China
mail: paoertang_2024@qq.com
* Correspondence: Zhong Fang, email: fazhong02@fjnu.edu.cn

Abstract: To accurately assess the significance of AI in smart city development, this paper proposes an Entropy Meta Two-stage Dynamic SBM model and introduces the "EIT-6S" framework. The framework initially evaluates the development level of AI technology through Environmental Support, Industrial Development, and Technological Innovation (EIT), and assesses the efficiency of SC development based on six aspects: Smart Technology, Smart Economy, Smart Citizen, Smart Governance, Smart Environment, and Smart Transportation (6S). This study also introduces Kernel Density Estimation, the Gravity Model, and the Standard Deviation Ellipse Model to examine the temporal and spatial divergence characteristics of the AI system, SC system, and AISC system. The findings are as follows: (1) The average overall efficiency of smart city systems in 30 Chinese provinces was 0.86 from 2019 to 2023. It shows a slight downward trend. AI technology investment limits the efficiency of SC development and is the main source of inefficiency. The shortage of R&D funds and talent is the main bottleneck. (2) To improve the overall efficiency of AISC systems, policymakers should focus on improving the performance of the AI systems in Jilin**,** Zhejiang, and Hubei, preventing the continuous decline of efficiency in Tianjin and Liaoning, and focusing on the SC systems in Chongqing and Hubei. (3) The overall inefficiency in Northeast China stems from the widening differences in the AI technology base within the province, while the level of SC in the central and western regions drags down the efficiency improvement. (4) The development of AI technology is undergoing the process of "agglomeration followed by diffusion". The gravity centre of AI has a potentially dominant role in the formation and development of the gravity centre of AISC.

Keywords: Smart Divide; AI Technology; Smart City; Spatial-temporal Divergence

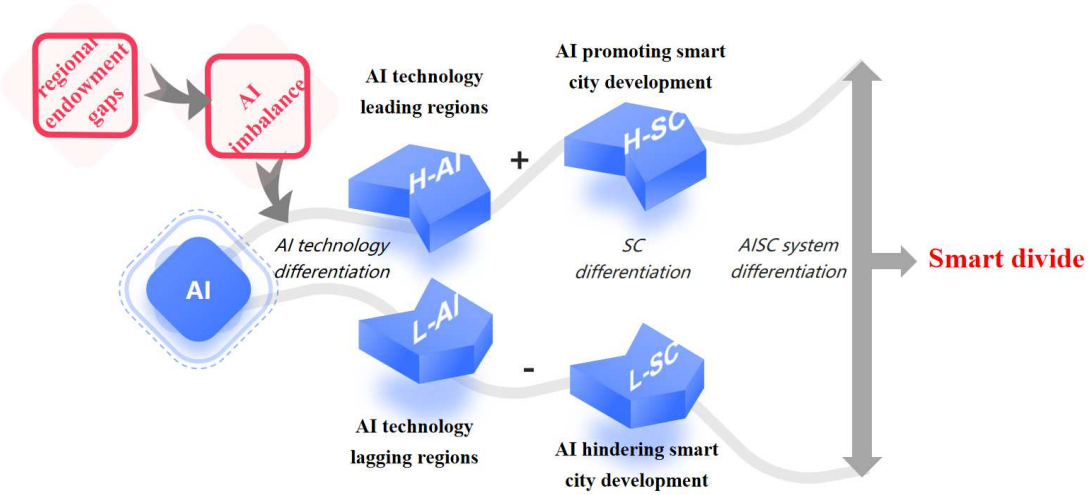
1. Introduction

China's urbanisation rate has risen from 26.41% in 1990 to 66.16% in 2023, and the high population density in cities has caused traffic congestion, environmental pollution, resource constraints and other systemic "urban diseases". In this context, the construction of smart cities has become a key path to solve chronic urban diseases and promote sustainable development (Lifelo et al., 2024). On one hand, it realises the dynamic and optimal allocation of urban resources through the in-depth application of IoT, big data, AI and other technologies. On the other hand, it directly drives the development of digital industry clusters, drives scientific and technological innovations, and fosters new economic growth (Liu et al., 2021). This transformation logic has been proven globally—cities such as Singapore and Copenhagen have significantly improved their international competitiveness through smart upgrading. Therefore, the promotion of smart city construction in China is not only a realistic need to tackle the challenges of urbanisation but also a strategic choice to seize the commanding heights of future development.

In recent years, AI technology has significantly improved the effectiveness of urban governance by optimising resource allocation and empowering intelligent decision-making. It has become the core engine driving the upgrading of smart cities. The application of AI technology in smart cities spans various areas, including the collection and analysis of urban data, infrastructure management, urban planning and design, urban intelligent transportation, environmental detection, disaster warning, intelligent security and smart home etc (Alsubai et al., 2024; Chen and Zhang, 2022; Fang et al., 2023; Zhang et al., 2021). As a specific example, AI technology can significantly reduce traffic congestion by 20% during peak hours by regulating intersection signals and controlling traffic flow (Jaramillo-Alcazar et al., 2023). This demonstrates the close relationship between AI technology and smart cities. AI not only enhances the intelligence of cities but also promotes sustainable development and safety management, making smart cities more efficient, convenient, and livable. However, the application of AI in cities also presents potential drawbacks, such as the displacement of traditional jobs, leading to unemployment. Furthermore, the collection of information and data by AI raises privacy concerns (Braun et al., 2018).

It is evident that the rapid development of AI technology is transforming the construction model of smart cities. An important issue arising from this is that, against the backdrop of uneven regional development in China, factors such as imbalances in economic foundations, industrial structures, computing infrastructure, talent concentration, and policy support have exacerbated inequalities in the penetration of AI technology, leading to regional disparities in AI technology (Hammerschmidt et al., 2025). Therefore, in this process, the uneven regional development of AI technology may give rise to a new smart divide. Specifically, due to the differentiation of AI technology, regions with leading AI technology will emerge alongside those lagging behind. As this differentiation widens, the efficiency gap in AI technology between regions will continue to expand. Regions with leading AI technology will benefit from AI-driven advancements, further enhancing their smart city development, while regions with lagging AI technology will face obstacles to their smart city development due to their low AI standards, potentially even offsetting the overall efficiency of smart city construction (Shu et al., 2024). The combination of AI-driven technological differentiation and SC amplification exacerbates AISC system differentiation (i.e., the further

widening of smart city development gaps), thereby creating a new smart divide. The framework diagram illustrating the formation of the smart divide is shown in Fig. 1. A study by Acemoglu and Restrepo (2021) on the US labour market reveals the "double-edged sword effect" of technological change: while AI can enhance productivity, if it is not sufficiently adapted to the region, it may lead to the replacement of low-skilled jobs by "automation". Their finding that "automation replaces low-skilled jobs" and exacerbates income inequality provides theoretical support for the risk of a smart divide. This paradox of positive and negative impacts carried by AI also suggests the need for a more refined efficiency assessment framework, which is why this paper incorporates AI technologies in the smart city development assessment framework.



Note: H-AI refers to high-efficiency AI. L-AI refers to low-efficiency AI.

Fig. 1. The formation of the smart divide.

Amina Mohammed, Deputy Secretary-General of the United Nations, warned at the UN General Assembly that if the international community does not act decisively, the digital divide will become the "new face of inequality (Costa, 2024). In the context of Smart Cities, the digital divide manifests at three levels: the Access Divide (differences in infrastructure accessibility), the Literacy Divide (differences in the ability to use digital skills and capabilities), and the Smart Divide (social inequalities and injustices caused by core AI technologies). It can be seen that the Smart Divide is a more integrated, complex and hidden advanced stage of the digital divide in the smart era.

Previously, China largely played the role of a follower in the pre-access and literacy chasm stages, both in terms of theoretical research and public policy. However, as China enters the smart divide period—especially catalysed by the COVID-19 pandemic—it is showing a unique opportunity for innovation breakthroughs. For instance, the "Health Code" system has achieved 1.4 billion people coverage, highlighting the potential for technological inclusion. It is important to note that the smart divide driven by the logic of capital in the smart era is only beginning to emerge. We currently know very little about its inherent patterns and potential risks (Yigitcanlar et al., 2020). The opportunities and challenges brought by AI technology to human beings have yet to be observed and researched. In the face of the deep divide that may be triggered by the explosive breakthrough of smart technologies, humans must prepare for it in the design of governance systems (Aditya et al., 2023; Caragliu and Del Bo, 2023).

The current literature on AI technology and smart cities exhibits several gaps: the lack of differential impacts of the dynamic penetration of AI technology on the efficiency of smart cities, the lack of attention to the "smart divide" exacerbated by the process of intelligence, and the lack of multidimensional evaluation of smart cities in terms of citizen and government dimensions. To address these issues and move beyond the static evaluation paradigm, this paper constructs an Entropy Meta Two-stage Dynamic SBM model and establishes the "EIT-6S" framework for the first time. This framework systematically evaluates the efficiency of smart city development from two dimensions. The first stage (EIT efficiency) focuses on the AI technology level composed of environmental support, industrial development and technological innovation. The second stage (6S efficiency) measures the efficiency of smart cities based on the system of smart technology, smart economy, smart citizen, smart governance, smart environment, and smart transport. This paper further combines the kernel density estimation, gravity model and standard deviation ellipse method to reveal the dynamic evolution of AI-driven smart city efficiency across 30 provinces in China from 2019-2023. This includes analysing the trajectory of efficiency trajectories in terms of regional differences and stage efficiencies, identifying the key variables of technological imbalances, and exploring how technological differences distort efficiency evolution. Only by clarifying the interaction mechanism of "regional differences - technology penetration - efficiency evolution - spatial differentiation" can we provide a policy of both resilience and inclusiveness for AI-enabled smart cities. The article framework diagram is shown in Fig. 2.

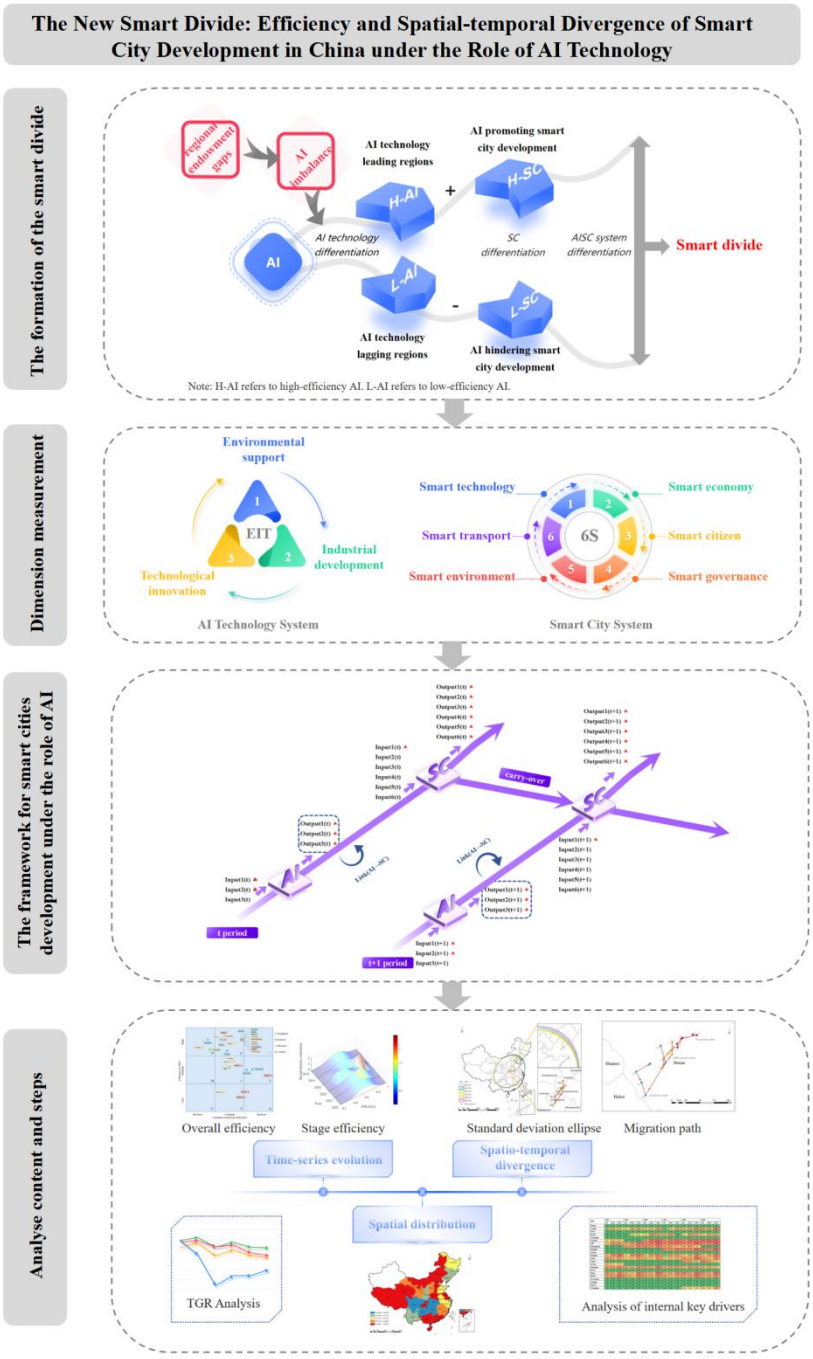


Fig. 2. Article framework diagram.

Narrowing regional economic development gaps, addressing the new "smart divide" triggered by AI technology, and building cities centred around people are crucial for ensuring the long-term effectiveness of smart city development. The main contributions of this study are as follows: **(1) Proposed and defined the concept of the "smart divide",** clarified its formation process, and verified its existence. (2) **Development of a Framework**: A framework is proposed to construct a two-stage model of "EIT technology foundation - 6S application effectiveness", which helps to understand the role of AI in China's smart city development. (3) **Comprehensive Evaluation of Smart Cities**: Evaluating smart cities from a more comprehensive 6S dimension, incorporating key criteria for smart city assessment and

development requirements. The 6S system adds "smart citizen" and "smart government" dimensions (including education expenditure, government transparency index, service supply capacity, etc.), which correct the tendency of "GDP only". (4) **Enriching Evaluation Tools**: The paper enhances the tools for evaluating smart city development efficiency under AI technology's influence. It proposes an Entropy Meta Two-stage Dynamic SBM model, which solves the problems of connectivity among decision-making units, regional differences and too many variables compared with the results of the traditional single-stage DEA model. In this paper, we further conduct a systematic study on the dynamic evolution of smart city efficiency driven by AI, improving the dynamic embedding perspective of AI technology for smart city efficiency evaluation. (5) **Policy Recommendations**: This paper provides detailed information to alert managers to formulate differentiated and forward-looking policies to guard against the smart divide.

2 Literature review

The conceptual development of smart cities has progressed in distinct stages. The concept of a "smart city" was formally proposed by International Business Machines Corporation (IBM) in 2010, emphasising the Internet of Things (IoT) as the core to facilitate the synergy between urban subsystems (Alahi et al., 2023). In 2012, China's Ministry of Housing and Urban-Rural Development, Ministry of Industry and Information Technology, and other relevant agencies incorporated smart cities into national policy and launched pilot initiatives. Early smart city research focused on the application of information technology to make cities smarter through infrastructure (Harrison et al., 2010; Wu and Yang, 2010). Since 2015, China has broken away from the IBM model and shifted to its path characterised by "new smart cities" with a "people-centred orientation", placing greater emphasis on enhancing citizens' sense of access and well-being (Ahvenniemi et al., 2017). In May 2024, four departments of the National Development and Reform Commission, the Ministry of Finance and the Ministry of Natural Resources jointly formulated the *Guidelines on Deepening the Development of Smart Cities and Promoting the Digital Transformation of Cities Nationwide*, which emphasised the need for smart cities to be promoted in "the whole area, in all directions, in the whole process" and "with their own characteristics".

Based on the above evolution, this paper defines a smart city as one that, with the support of new-generation information technology (e.g., IoT, big data, and AI), carries out real-time sensing, interconnection and sharing, and intelligent analysis of key information of the core system of urban operation, to comprehensively integrate urban resources and provide citizens with more convenient and efficient social services and more scientific and intelligent urban management.

Academic research on smart city assessment lags behind the development of smart cities. Existing studies mainly focus on the following areas:

(a) Evaluating the implementation effects of smart city pilot policies. Chinese scholars mostly focus on the impact of smart city construction on economic variables, such as regional employment and income, total factor productivity, and technological innovation (Chen et al., 2024; Li et al., 2024; Ling et al., 2023; Song et al., 2021; Song et al., 2022; Wan and Cui, 2025). However, fewer studies directly assess the construction outcomes of smart cities themselves. In terms of research methodology, the Differences-in-Differences(DID) in quasi-natural experiments is commonly adopted (Xia et al., 2023). This approach has a significant limitation.

It simply divides smart city implementation into a binary state of "yes" and "no", ignoring the variability of policy intensity, resource investment, and depth of technology application in different regions. Allam and Dhunny (2019) questioned the use of the DID model in smart city assessment, with the central point being that the essence of a city's "smartness" is not in its labelling, but in how effectively the technology connects with local systems and meets citizens' needs. In the Chinese context, sample selection bias is another key problem. Many studies delineated the scope of the study solely based on the three pilot lists published by the Ministry of Housing and Urban-Rural Development (2012-2014, about 150 prefecture-level cities). In reality, China's smart city pilots involve multiple levels of administrative units. When cross-sectoral pilots are included, the total number of participating cities—covering prefectures, municipal districts, and county-level units—approaches 900. Therefore, this assessment method cannot fully reflect the real implementation effect of national smart city policies. There may be sample selection bias that underestimates the impact of the policy on small and medium-sized cities and county areas. Moreover, it overlooks the heterogeneity in smart city development across different city types.

(b) Research on the difficulties and solutions in smart city construction. Some scholars have focused on the theoretical level to analyse the practical difficulties and breakthrough paths of smart city construction. Existing studies have pointed out that the construction of smart cities faces multidimensional structural dilemmas. At the technical level, there is the problem of "data silos" caused by the administrative system, and a large amount of data has not been transformed into regular knowledge (Fang and Xu, 2022; Li et al., 2024). There are also insufficient infrastructure sharing, privacy leakage and security issues (Allam and Jones, 2020; Singh et al., 2020). At the institutional level, there is a lack of top-level design, barriers to cross-industry and cross-business cooperation, and a lack of a sound mechanism for balancing interests (Yan et al., 2023). In this regard, scholars have proposed a systematic framework of countermeasures. This includes improving the systematic policy support system through national strategies, breaking down data barriers through institutional innovation, city governments, and effectively transforming functions so that urban residents can become the centre of the city (Skubis et al., 2024). Notably, there has been a paradigm shift in the role of the citizen. Early studies focused on technology-driven practice paths, and more recently there has been a gradual shift towards a multifaceted governance model that emphasises social collaboration and citizen participation (Preston et al., 2020; Zheng and Sieber, 2021).

(c) Research on smart city assessment systems. Smart city assessment system research has experienced a paradigm shift from a single dimension to system integration, forming an evaluation framework covering multiple dimensions (Lombardi et al., 2012; Qian et al.). Some studies focus on single application scenarios, such as smart education public service evaluation, and smart building evaluation(Molnar, 2021; Shahrabani and Apanaviciene, 2024). To break through the fragmentation limitations, Cui and Yang (2018) constructed a multidimensional smart city building evaluation index system, with human capital, infrastructure, and capital investment as inputs, and the four dimensions of smart government, smart economy, smart life, and smart humanistic literacy as outputs. However, this study remains theoretical and does not evaluate the actual outcomes of smart city construction. Since the evaluation objects are all multiple cities, the indicator systems for different application levels lack evaluation indicators that reflect the characteristics of the cities (Wang

and Zheng, 2013). Liu (2024) points out that ignoring this urban heterogeneity can lead to unfair evaluation results, especially for some evaluation work that serves the government's performance appraisal.

Although existing studies have extensively explored the policy effects and development paths of smart cities, and the computer field has confirmed the potential for deep integration of AI and urban systems (Manman et al., 2021), there are three main gaps in the academic focus. First, most studies overlook the differential impact of the dynamic penetration of AI technologies on the efficiency of smart cities (Bokhari and Myeong, 2023). Second, while some literature examines the process and drawbacks of AI application in smart cities (Guo, 2024; Ullah et al., 2020), less attention has been paid to the institutional adaptability of AI technologies to smart cities, especially the lack of attention to the smart divide that may be created. Technically, "AI+Big Data" needs to be further improved in terms of smart city data governance (Zhou et al., 2025). For example, mountainous cities are forced to reduce deployment density due to the high energy consumption of visual IoT devices, which in turn widens the governance capability gap with developed regions (El Ghati et al., 2024). The Smart Divide emerges when the application of AI technologies within cities instead increases regional inequalities. Thirdly, there is an absence of the citizen and government dimensions of multidimensional evaluation in smart city assessment (Ringenson et al., 2017). Vanolo (2014) argues that the tendency towards technological determinism in smart city assessment masks the role of institutional fitness. Under the guise of "efficiency" and "optimisation", social issues are reduced to mere technological problems, neglecting the importance of democratic participation and social equity.

3. Modelling and methodology

In 2001, Tone proposed the Slacks-Based Measure (SBM) model, which uses slacks as the basis of measurement, takes into account the slack between inputs and outputs, and presents the SBM efficiency in a non-radial estimation mode and scalar (Tone, 2001). Tone and Tsutsui (2009) then propose a weighted slack-based measures network data envelopment analysis model, which takes the linkage between the various departments of the decision-making unit as the analytical basis of the network DEA model, and treats each department as a sub-division. The linkage between the departments of a decision-making unit is used as the basis of the network DEA model, and each department is considered as a Sub-DMU, and then the SBM model to find the optimal solution. In 2014, Tone and Tsutsui (2014) further developed this idea by introducing the weighted slack-based measures dynamic network DEA data envelopment analysis model. This model takes the linkage between the departments of the decision-making unit as the basis of analysis. The departments are regarded as Sub-DMU, and the carry-over activities are regarded as the linkage. However, the dynamic network DEA model of Tone and Tsutsui (2014) does not address issues related to regional differences and an excessive number of variables. To resolve this, this paper integrates Shannon’s (1948) Entropy with the dynamic network DEA model of Tone and Tsutsui (2014) and the meta-frontier model of O'Donnell et al. (2008) to proposed the Entropy Meta Two-stage Dynamic SBM model.

3.1. Entropy method

In this assessment model, some input-output indicators have multidimensional characteristics, which can lead to biased efficiency assessments if directly applied to the DEA

model.To address this limitation, this paper introduces the information entropy theory, using Shannon's (1948)entropy method to perform dimensionality reduction and comprehensive quantification of multidimensional indicators. Table 1 presents the indicators used in this paper, indicating whether each input and output indicator has been processed using the entropy method, along with the detailed indicators synthesized through this process. The average weight of each index using entropy method is also listed in the table. Since this is only an auxiliary method for this study, the detailed steps of the entropy method are shown in Appendix A.

Table 1

Indicators for each stage.

Dimension	Symbol	Entropy	Detailed indicators	Weight
AI technology development				
Environment support	Input1	Yes	Statistical incubators (units)	0.1234
			R&D organisations for high-tech industries (units)	0.2642
			Full-time equivalent of R&D personnel (persons)	0.1226
			Employees in information transmission, software and information technology services (persons)	0.1418
			Equivalent full-time equivalents of R&D personnel in high-tech industries (persons)	0.2083
			Mobile phone penetration rate (%)	0.0694
			Fixed asset investment in information transmission, computer services and software industry (billion yuan)	0.0703
	Output1	Yes	New product development projects in high-tech industry (items)	0.6163
			Length of long-distance fibre-optic cable lines (km)	0.1819
			Internet broadband access ports (ten thousand units)	0.2018
Industrial development	Input2	Yes	Technical production (units)*	0.1707
			Computers used by enterprises at year-end (units)	0.1378
			Enterprise-owned websites (units)	0.1320
			Expenditure on new product development (million yuan)	0.2720
			Expenditure on technological transformation (million yuan)	0.2874
	Output2	Yes	Main business revenue (billion yuan)	0.3919
			Total profit (billion yuan)	0.3655
			Artificial Intelligence Enterprises (units)	0.2427
Technology innovation	Input3	No	External R&D expenditure (million yuan)	
	Output3	Yes	Scientific papers indexed by major retrieval tools (papers)	0.1452
			Artificial Intelligence Patent Application and Acquisition (items)	0.2565
			Sales Revenue of New Products Developed by High-Tech Industries (million yuan)	0.3117
			Software business revenue (billion yuan)	0.2866
Smart city development				
Smart technology	Input1	Yes	Internet development-number of domain names (ten thousand units)	0.5182
			Length of fibre optic cable lines (km)	0.2523
			Mobile phone base stations (million units)	0.2294
	Output1	Yes	Proportion of enterprises with e-commerce trading activities (%)	0.3060
			Total telecommunications business (billion yuan)	0.3768
			Mobile phone subscribers at year-end (million households)	0.3173
Smart economy	Input2	No	Expenditure on science and technology (million yuan)	
	Output2	Yes	Revenue of innovation industry (million yuan)	0.2724
			Innovation R&D patents (units)	0.2185
			Percentage of enterprises carrying out innovation activities (%)	0.0567
			Scale of e-commerce (billion yuan)	0.2090
			Personnel engaged in technological R&D (persons)	0.2434
Smart citizen	Input3	No	Education expenditure (million yuan)	
	Output3	Yes	Students enrolled in higher education per 10,000	0.0844

Dimension	Symbol	Entropy	Detailed indicators	Weight
			population (persons)	
			Proportion of personnel in information transmission, software and information technology services (%)	0.5944
			Proportion of personnel in scientific research and technical services (%)	0.3212
Smart governance	Input4	No	General public services (million yuan)	
	Output4	Yes	Government Transparency Index	0.2909
			Service Supply Capacity Index	0.2088
			Service Responsiveness Index	0.2852
			Service Intelligence Capability Index	0.2151
Smart environment	Input5	No	Environmental protection expenditure (million yuan)	
	Output5	Yes	Energy Intensity (tonnes of standard coal/million yuan)	0.0764
			Waste gas emissions (tonnes/million yuan)	0.0642
			Carbon dioxide emissions (tonnes)	0.0857
			Waste utilisation rate (%)	0.2459
			Sewage treatment rate (%)	0.1022
			Harmless treatment rate of domestic waste (%)	0.0536
			Greening coverage rate of built-up areas (%)	0.1410
			Forest coverage rate (%)	0.2309
Smart transportation	Input6	No	Transportation expenditure (million yuan)	
	Output6	Yes	Land used for transportation (million hectares)	0.1880
			Total passenger volume (10,000 persons)	0.2373
			Total freight volume (million tonnes)	0.2352
			Railway operating mileage (km)	0.1617
			Highway mileage (km)	0.1778

*: Calculation: Based on the number of industrial robots installed in each industry in China published by IRF Alliance, collect the percentage of employment in each province of the sub-sector to the total employment in the whole country from the China Labour Statistics Yearbook, and get the result from "the percentage×the number of robots installed in each industry in the whole country".

3.2. Entropy meta two-stage dynamic SBM model

3.2.1 Symbol description

Fig. 3 shows the efficiency framework of China's smart city development under AI technology, where the input or output indicators with "▲" are synthesised using the method in Section 3.1. We deal with n DMUs in T periods, and each decision unit has two stages, the artificial intelligence (AI) technology development stage and the smart city (SC) development stage. In the AI stage, there are three inputs and outputs dimensions: environmental support, industrial development, and technological innovation. In the SC stage, there are six inputs and outputs dimensions: smart technology, smart economy, smart citizen, smart governance, smart environment, and smart transport. The outputs of the AI stage are also regarded as intermediate product (Link) inputs to the SC stage.

Suppose there are n DMUs (o=1,...,n), k stages (k=1,...,K) and T periods of time (t=1,...,T). Each DMU has its own input and output terms. In each t period, it is linked to the next t+1 period through carry-over simultaneously. Let m_k and r_k represent the inputs and outputs in each k stage, with $(k,\mathrm{h})_i$ represents the period from k to h. $L_{\mathrm{h}k}$ is the k and h division set. The definitions of inputs, outputs, links and carry-over are summarised in Table 2 below.

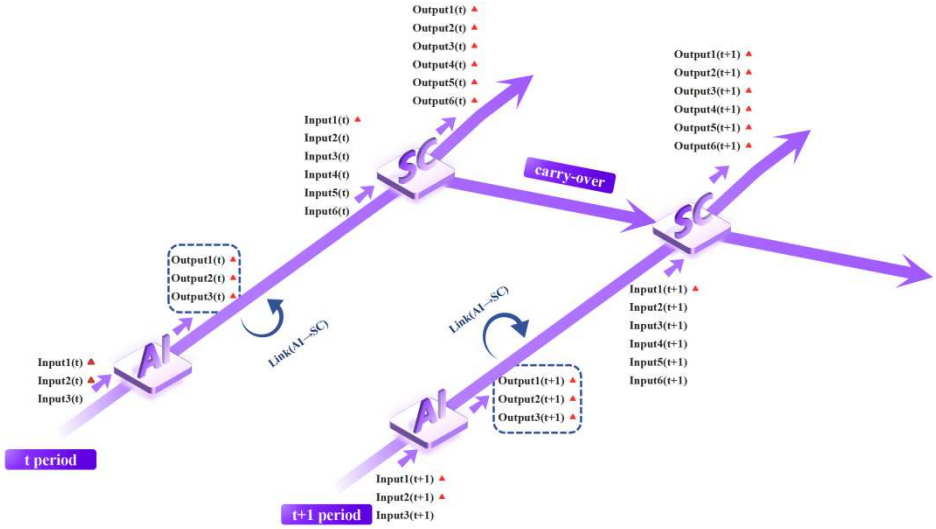


Fig. 3. Efficiency framework.

Table2

Variable symbols.

Inputs	$IN^t_{iok} \epsilon R_+ (i=1,\ldots,m_k;\ o=1,\ldots,n;\ k=1,\ldots,K;\ t=1,\ldots,T)$ refers to input i at time period t for DMU_o division k.						
Stage AI	$IN1^t_{iok}$	i=1	Environmental support-input▲	**Stage SC**	$IN2^t_{iok}$	i=1	Smart technology-input▲
		i=2	Industrial development-input▲			i=2	Expenditure on science and technology
		i=3	External R&D expenditure			i=3	Education expenditure
						i=4	General public services
						i=5	Environmental protection expenditure
						i=6	Transportation expenditure
Outputs	$OUT^t_{rok} \epsilon R_+ (r=1,\ldots,r_k;\ o=1,\ldots,n;\ k=1,\ldots,K;\ t=1,\ldots,T)$ refers to output r in time period t for DMU_o division k.						
Stage AI	$OUT1^t_{rok}$	r=1	Environmental support-output▲	**Stage SC**	$OUT2^t_{rok}$	r=1	Smart technology-output▲
		r=2	Industrial development-output▲			r=2	Smart economy-output▲
		r=3	Technological innovation-output▲			r=3	Smart citizen-output▲
						r=4	Smart governance-output▲
						r=5	Smart environment-output▲
						r=6	Smart transportation-output▲
Links	$LN^t_{do(kh)}\ \epsilon R_+ (d=1\ldots D;o=1,\ldots,n;(kh)=1,\ldots,\ link\ ;\ t=1,\ldots,T)$ are the period t links from DMU_o division k to division h, with (kh) being the number of k to h links.						
Stage AI and Stage SC	$LN^t_{do(12)}$	d=1	Environment support-output▲				
		d=2	Industrial development-output▲				
		d=3	Technology innovation-output▲				
Carry-overs	$Z^{(t,t+1)}_{cok_l} \epsilon R_+ (c=1\ldots.C;o=1,\ldots,n;\ k_l=1,\ldots,\ ninput;\ t=1,\ldots,T-1)$ refers to the carry-over of t to the $t+1$ period from DMU_o division k to division h, with L_k being the number of carry-over items in division k.						
	$Z^{(t,t+1)}_{cok_l}$	c=1	Net value of fixed assets				
Slacks				**Other variables**			
	s^{t-}_{iok} *and* s^{t+}_{rok}		Input and output slacks	$W^t(t=1\ldots T)$			The weight to period t
	$s^{t-}_{do(kh)}$		Link slacks	$W^k(k=1\ldots k)$			The weight to division k
	$s^{t(t,t+1)}_{cok_l}$		Carry-over slacks				

Notes: "▲"stands for index synthesized by entropy method.

3.2.2 Objective function

(1) Meta-frontier (MF)

Suppose Each of the DMU_p has an input and output at time period t and a carry-over (link) to the next t+1 time period. Due to differences in management type, resources, regulations, or environment, all provinces(N) consist of decision-making units in the cluster g ($N=N_1+N_2+$ .....$+N_G$). In this study, all decision-making units are divided into 4 groups, so G=4. $X_{io}$and y_{ro} represent the i-th input (i=1,…,m_k) and the r-th final output r (r=1,…,r_k) of the o-th unit (o=1,…,n) respectively. Under the meta frontier, DMU_o can maximise its efficiency value by choosing the optimal output weights to maximise its efficiency value, hence the efficiency of DMU_o under the meta frontier can be solved by the following linear programming procedure.

(a) Objective function

Overall efficiency:

$$\theta_p^*=min\frac{\sum_{t=1}^{T}W^t\left[\sum_{k=1}^{K}W^k\left[1-\frac{1}{m_k+ninput_k}\left(\sum_{g=1}^{G}\sum_{i=1}^{m_k}\frac{s_{gipk}^{t-}}{x_{gipk}^{t}}+\sum_{g=1}^{G}\sum_{k_l}^{ninput_k}\frac{s_{gcpk_l}^{(t,t+1)}}{z_{gcpk_l}^{(t,t+1)}}\right)\right]\right]}{\sum_{t=1}^{T}W^t\left[\sum_{k=1}^{K}W^k\left[1+\frac{1}{r_k+link_k}\left(\sum_{g=1}^{G}\sum_{r=1}^{r_k}\frac{s_{grpk}^{t+}}{y_{grpk}^{t}}+\sum_{g=1}^{G}\sum_{(kl)}^{link_k}\frac{s_{gdp(kl)}^{t}}{z_{gdp(kl)}^{t}}\right)\right]\right]} \quad (1)$$

$$\sum_{t=1}^{T}W^t=1;\sum_{k=1}^{K}W^k=1.$$

Subject to:

Stage 1: AI stage	**Stage 2:** SC stage
$IN1_{gip1}^{t}=\sum_{g=1}^{G}\sum_{o=1}^{n}IN1_{gio1}^{t}\lambda_{gio1}^{t}+s_{gip1}^{t-}$	$IN2_{gip2}^{t}=\sum_{g=1}^{G}\sum_{o=1}^{n}IN2_{gio2}^{t}\lambda_{gio2}^{t}+s_{giop}^{t-}$
(i=1,…,m_k,g=1…..G)	(i=1,…,m_k,g=1…..G)
$OUT1_{grp1}^{t}=\sum_{g=1}^{G}\sum_{o=1}^{n}OUT1_{gro1}^{t}\lambda_{gro1}^{t}-s_{grp1}^{t+}$	$OUT2_{grp2}^{t}=\sum_{g=1}^{G}\sum_{o=1}^{n}OUT2_{gro2}^{t}\lambda_{gro2}^{t}-s_{grp2}^{t+}$
(r=1,…,r_k,g=1…..G)	(r=1,…,r_k;g=1…..G)
$LN_{gdo(12)}^{t}=\sum_{g=1}^{G}\sum_{o=1}^{n}LN_{gdo(12)}^{t}\lambda_{gdo(12)}^{t}-s_{gdp(12)}^{t-}$	$\lambda_{gio2}^{t}\geq0,\ \lambda_{gro2}^{t}\geq0;\ \lambda_{gdo(21)}^{t}\geq0$
(d=1…D;g=1…..G)	$s_{gip2}^{t-}\geq0,\ s_{grp2}^{t+}\geq0$
$\lambda_{gio1}^{t}\geq0,\ \lambda_{gro1}^{t}\geq0;\ \lambda_{gdo(12)}^{t}\geq0$	$e\lambda_{k}^{t}=1\ \ (\forall k,\forall t)$
$s_{gip1}^{t-}\geq0,\ s_{grp1}^{t+}\geq0\ ;\ s_{gdp(12)}^{t-}\geq0$	$Z_{gcpk_l}^{(t,t+1)}=\sum_{g=1}^{G}\sum_{o=1}^{n}Z_{gcok_l}^{(t,t+1)}\lambda_{gco\,k_l}^{t}+s_{gcpk_l}^{t(t,t+1)}$
	(c=1…C,g=1…..G)
	$s_{gpk_l}^{t(t,t+1)}\geq0$

(b) Period and division efficiencies

The period and division efficiencies are as follows.

(b1) Period efficiency:

$$\partial_p^* = min \frac{\sum_{k=1}^{K} W^k \left[1 - \frac{1}{m_k + ninput_k} \left(\sum_{g=1}^{G} \sum_{i=1}^{m_k} \frac{s_{gipk}^{t-}}{x_{gipk}^t} + \sum_{g=1}^{G} \sum_{k_l}^{ninput_k} \frac{s_{gcpk_l}^{(t,t+1)}}{z_{gcpk_l}^{(t,t+1)}} \right) \right]}{\sum_{k=1}^{K} W^k \left[1 + \frac{1}{r_k + link_k} \left(\sum_{g=1}^{G} \sum_{r=1}^{r_k} \frac{s_{grpk}^{t+}}{y_{grpk}^t} + \sum_{g=1}^{G} \sum_{(kl)}^{link} \frac{s_{gdp(kl)}^t}{Z_{gdp(kl)}^t} \right) \right]} \quad (2)$$

(b2) Division efficiency:

$$\varphi_p^* = min \frac{\sum_{t=1}^{T} W^t \left[1 - \frac{1}{m_k + ninput_k} \left(\sum_{g=1}^{G} \sum_{i=1}^{m_k} \frac{s_{gipk}^{t-}}{x_{gipk}^t} + \sum_{g=1}^{G} \sum_{k_l}^{ninput_k} \frac{s_{gcpk_l}^{(t,t+1)}}{z_{gcpk_l}^{(t,t+1)}} \right) \right]}{\sum_{t=1}^{T} W^t \left[1 + \frac{1}{r_k + link_k} \left(\sum_{g=1}^{G} \sum_{r=1}^{r_k} \frac{s_{grpk}^{t+}}{y_{grpk}^t} + \sum_{g=1}^{G} \sum_{(kl)}^{link_k} \frac{s_{gdp(kl)}^t}{Z_{gdp(kl)}^t} \right) \right]} \quad (3)$$

(b3) Division period efficiency:

$$\rho_p^* = min \frac{\left[1 - \frac{1}{m_k + ninput_k} \left(\sum_{g=1}^{G} \sum_{i=1}^{m_k} \frac{s_{gipk}^{t-}}{x_{gipk}^t} + \sum_{g=1}^{G} \sum_{k_l}^{ninput_k} \frac{s_{gcpk_l}^{(t,t+1)}}{z_{gcpk_l}^{(t,t+1)}} \right) \right]}{\left[1 + \frac{1}{r_k + link_k} \left(\sum_{g=1}^{G} \sum_{r=1}^{r_k} \frac{s_{grpk}^{t+}}{y_{grpk}^t} + \sum_{g=1}^{G} \sum_{(kl)}^{link_k} \frac{s_{gdp(kl)}^t}{Z_{gdp(kl)}^t} \right) \right]} \quad (4)$$

From the above, the overall efficiency, period efficiency, division efficiency, and division period efficiency can be obtained using the meta-frontier model.

(2) Group-frontier (GF)

As each DMU under the group frontier chooses the most favorable final weighted output, the DMU efficiencies under the group frontier are solved using the following equations:

(a) The objective function

Overall efficiency:

$$\theta_p^{g*} = min \frac{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} W^k \left[1 - \frac{1}{m_k + ninput_k} \left(\sum_{i=1}^{m_k} \frac{s_{ipk}^{t-}}{x_{ipk}^t} + \sum_{k_l}^{ninput_k} \frac{s_{cpk_l}^{(t,t+1)}}{z_{cpk_l}^{(t,t+1)}} \right) \right] \right]}{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} W^k \left[1 + \frac{1}{r_k + link_k} \left(\sum_{r=1}^{r_k} \frac{s_{rpk}^{t+}}{y_{rpk}^t} + \sum_{(kl)}^{link_k} \frac{s_{dp(kl)}^t}{Z_{dp(kl)}^t} \right) \right] \right]} \quad (5)$$

$$\text{with} \sum_{t=1}^{T} W^t = 1; \sum_{k=1}^{K} W^k = 1.$$

Subject to:

Stage 1: AI stage	**Stage 2:** SC stage
$IN1_{ip1}^t = \sum_{o=1}^{n} IN1_{io1}^t \lambda_{io1}^t + s_{ip1}^{t-}$	$IN2_{ip2}^t = \sum_{o=1}^{n} IN2_{io2}^t \lambda_{io2}^t + s_{ip2}^{t-}$
$(i=1,\ldots,m_k)$	$(i=1,\ldots,m_k)$
$OUT1_{rp1}^t = \sum_{o=1}^{n} OUT1_{ro1}^t \lambda_{ro1}^t - s_{rp1}^{t+}$	$OUT2_{rp2}^t = \sum_{o=1}^{n} OUT2_{ro2}^t \lambda_{ro2}^t - s_{rp2}^{t+}$
$(r=1,\ldots,r_k)$	$(r=1,\ldots,r_k)$

$LN^{t}_{dp(12)}=\sum_{o=1}^{n} LN^{t}_{do(12)}\lambda^{t}_{do(12)}-s^{t-}_{dp(12)}$	$\lambda^{t}_{io2}\geq 0,\ \lambda^{t}_{ro2}\geq 0;\lambda^{t}_{do(21)}\geq 0$
(d=1…D)	$s^{t-}_{ip2}\geq 0,\ s^{t+}_{rp2}\geq 0$
	$e\lambda^{t}_{k}=1\ \ (\forall k, \forall t)$
$\lambda^{t}_{io1}\geq 0,\ \lambda^{t}_{ro1}\geq 0;\ \lambda^{t}_{do(12)}\geq 0$	$Z^{(t,t+1)}_{cpk_l}=\sum_{o=1}^{n} Z^{(t,t+1)}_{cok_l}\lambda^{t}_{cok_l}+s^{t(t,t+1)}_{cpk_l}$ (c=1...C)
$s^{t-}_{ip1}\geq 0,\ s^{t+}_{rp1}\geq 0;\ s^{t-}_{dp(12)}\geq 0$	$s^{t(t,t+1)}_{cpk_l}\geq 0$

(b) Period and division efficiencies

The period and division efficiencies are as follows:

(b1) Period efficiency:

$$\partial^{*}_{p}=\min \frac{\sum_{k=1}^{K} W^{k}\left[1-\frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{s^{t-}_{ipk}}{x^{t}_{ipk}}+\sum_{k_l}^{ninput_k}\frac{s^{(t,t+1)}_{cpk_l}}{z^{(t,t+1)}_{cpk_l}}\right)\right]}{\sum_{k=1}^{K} W^{k}\left[1+\frac{1}{r_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s^{t+}_{rpk}}{y^{t}_{rpk}}+\sum_{(kl)}^{link}\frac{s^{t}_{dp(kl)}}{Z^{t}_{dp(kl)}}\right)\right]} \tag{6}$$

(b2) Division efficiency:

$$\varphi^{*}_{p}=min \frac{\sum_{t=1}^{T} W^{t}\left[1-\frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{s^{t-}_{ipk}}{x^{t}_{ipk}}+\sum_{k_l}^{ninput_k}\frac{s^{(t,t+1)}_{cpk_l}}{z^{(t,t+1)}_{cok_l}}\right)\right]}{\sum_{t=1}^{T} W^{t}\left[1+\frac{1}{r_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s^{t+}_{rpk}}{y^{t}_{rpk}}+\sum_{(kl)}^{link}\frac{s^{t}_{dp(kl)}}{Z^{t}_{dp(kl)}}\right)\right]} \tag{7}$$

(b3) Division period efficiency:

$$\rho^{*}_{p}=min \frac{1-\frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{s^{t-}_{ipk}}{x^{t}_{ipk}}+\sum_{k_l}^{ninput_k}\frac{s^{(t,t+1)}_{cpk_l}}{z^{(t,t+1)}_{cpk_l}}\right)}{1+\frac{1}{r_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s^{t+}_{rpk}}{y^{t}_{rpk}}+\sum_{(kl)}^{link}\frac{s^{t}_{dp(kl)}}{Z^{t}_{dp(kl)}}\right)} \tag{8}$$

From the above results, the overall efficiency, the period efficiency, the division efficiency and division period efficiency are obtained.

3.3. Technology gap ratio (TGR)

As the meta-frontier model contains g groups, the technical efficiency of the meta-frontier (MFE) is less than the technical efficiency of the group frontier (GFE). The ratio value, or the technology gap ratio (TGR), is:

$$\mathrm{TGR}=\frac{\theta^{*}_{p}}{\theta^{g*}_{p}}=\frac{MFE}{GFE} \tag{9}$$

3.4. Nonparametric kernel density estimation

This paper analyses the distributional dynamics of smart city development efficiency using Nonparametric kernel density estimation, which is a probability density function estimation method that does not require assumptions about the form of the data distribution. By superimposing the kernel function around each data point, a continuous probability

density curve is constructed to reflect the distribution form of the random variable. The kernel density function of the random variable X is:

$$f(x)=\frac{1}{n\mathrm{h}^{d}}\sum_{j=1}^{n}K\left(\frac{x-X_i}{\mathrm{h}}\right) \tag{10}$$

where n is the number of sample observations, d is the dimension of x, $X_1,\cdots,X_n$ is the efficiency value of each province, x is the mean value, and $K(\cdot)$ is the kernel density estimation function with bandwidth h. Changes in the height of the kernel density curve's peak reflect the degree of clustering in smart city development efficiency. A higher peak indicates greater concentration of the data. The number of peaks reflects the convergence or polarisation phenomenon of efficiency, single peak reflects the efficiency distribution of homogeneous groups, and multiple peaks reflect the efficiency distribution of different levels of multiple subgroups. The position of the main peak reflects the concentration trend of the data. Changes in the length of the left and right trailing tails of the curve reflect changes in the gap in the efficiency of smart city development.

3.5. Centre of gravity model

To understand the characteristics of the spatial distribution of efficiency and the trend of change, this paper uses the centre of gravity model to observe the movement path of the efficiency gravity centre. The centre of gravity reflects the point that keeps the efficiency level of each province balanced in all directions. During the study period, provinces with higher efficiency tend to "pull" the centre of gravity towards their regions. Assuming that the study area lies on a homogeneous plane (Luo et al., 2022) , and the efficiency centre of each province is located in the capital city, the coordinates of the efficiency gravity centre of province j in period t are:

$$\overline{x}_t=\sum_{j=1}^{n}w_{jt}x_j/\sum_{j=1}^{n}w_{jt} \tag{11}$$

$$\overline{y}_t=\sum_{j=1}^{n}w_{jt}y_j/\sum_{j=1}^{n}w_{jt} \tag{12}$$

Where $(\overline{x}_t,\overline{y}_t)$ is the spatial location coordinates of province j (j = 1, 2,⋯ , n), and w_{jt} is the weight (smart city efficiency value of province j in period t).

The jump distance and direction coordinates of the efficiency centre of gravity from $(\overline{x}_t,\overline{y}_t)$ to $(\overline{x}_{t'},\overline{y}_{t'})$ to during the study period are:

$$(Dis_{it'},\vartheta_{it'})=\left\{R\sqrt{(\overline{y}_t-\overline{y}_{t'})^2+(\overline{x}_t-\overline{x}_{t'})^2}),n\pi/2+arctan\left[(\overline{y}_t-\overline{y}_{t'})/(\overline{x}_t-\overline{x}_{t'})\right]\right\} \tag{13}$$

Where R is the conversion coefficient between latitude and longitude coordinates and plane distance, which takes the value of 111.11 by drawing on the study of Lu et al. (2013)When $\vartheta_{it'}=0$, the migration direction of the centre of gravity of the smart city efficiency is due east; and when$0<\vartheta_{it'}<90$, the migration direction is north-east, and this is deduced counter-clockwise.

3.6. Standard deviational ellipse model

Standard Deviational Ellipse (SDE) assesses the degree of dispersion of data by calculating the difference between the data points and the mean. Changes in parameters such as the rotation angle of the SDE and the ratio of the short and long axes can reflect the spatial and temporal evolution trajectories of the measured elements (Mao et al., 2022) , and its formula is set as follows:

$$\delta_{xt}=\sqrt{2}\sqrt{\frac{\sum_{j=1}^{n}(\overline{x}_t cos\theta-\overline{y}_t sin\theta)^2}{n}} \tag{14}$$

$$\delta_{yt}=\sqrt{2}\sqrt{\frac{\sum_{j=1}^{n}(\bar{x}_t sin\theta+\bar{y}_t cos\theta)^2}{n}} \quad (15)$$

θ is the azimuth of the standard deviation ellipse, representing the angle of clockwise rotation from the north to the ellipse's major axis. δ_{xt} and δ_{yt} are the standard deviation of the long and short axes, respectively. The standard deviation of the long axis reflects the degree of efficiency clustering in the dominant direction, and the standard deviation of the short axis reflects the range of efficiency distribution in the secondary direction. The smaller the standard deviation ellipse area is, the smaller the standard distance of X axis and Y axis is, indicating the stronger degree of agglomeration of the research object. In this paper, the output ellipse size is selected as 1 standard deviation, and about 68% of the data can be covered.

4. Indicator selection and data description

In line with the principles of scientific rigour and comprehensiveness, this study constructs AI technology development efficiency based on three dimensions, including environmental support, industrial development, and technological innovation. The evaluation system of smart city development efficiency is constructed from six dimensions, including smart technology, smart economy, smart citizen, smart governance, smart environment, and smart transport. The definition of each dimension is shown in Table 3. Specific indicators for each stage of the system are shown in Table 1 in 3.1.

This study uses data from 30 provincial-level regions in China from 2018 to 2023. Due to missing data, Xinjiang is excluded from the analysis. Individual missing values are filled in using the exponential smoothing method. There are significant differences in regional economic development levels across China. In order to avoid the "masking effect" of developed regions on the overall analysis, and to ensure that provinces at different stages of development can be fairly assessed, four regional groupings, namely Northeast, East, Central, and West, are used in assessing the level of smart city development. This grouping is consistent with the "four sectors" that have long been used in China's official statistics and regional policies. The specific samples and groupings are shown in Table 4.

The data used come from China Science and Technology Database, China Macroeconomic Database, China High-Tech Industry Database, China Education Statistics Database, China Urban and Rural Development Statistics Database, and China Urban and Rural Development Statistics Database. Database, China Urban and Rural Development Database, China Macroeconomic Statistics Database, China Stock Market & Accounting Research Database (CSMAR). Database, China Macroeconomic Statistics Database, China Stock Market & Accounting Research Database (CSMAR). The descriptive statistics of the data for each indicator are presented in Appendix Table A1. The minimum coefficient of variation (C.V.) is 0.17, occurs for the smart governance output index in the SC stage, indicating that the distribution of this index is relatively concentrated over the study period. On the contrary, the index at the AI stage has a higher fluctuation relative to its mean value. This indicates that the index has significant variation characteristics and can provide valuable information, verifying that it is necessary to incorporate AI technical indicators in the smart city system.

Table 3

Definition of smart city development efficiency indicators.

Indicator	Definition	Reference
AI technology development		
Environmental support	Measures the basic support conditions for AI technology development, reflecting regional policy support and market environment for AI technology R&D and application.	(Kourtit et al., 2021; Kourtit et al., 2023; Su et al., 2022)
Industrial development	Assesses the application of AI technology in actual industries, covering the level of industrial intelligence, enterprise informatisation and the market performance of high-tech industries.	(Chao et al., 2019; Ye et al., 2022; Zhang and Deng, 2023)
Technological innovation	Measures the R&D input and innovation output in the AI field, reflecting the originality and competitiveness of regional AI technology.	(Kocisova et al., 2024; Liu et al., 2020; Wojewnik-Filipkowska et al., 2024; Xu and Lin, 2025)
Smart city development		
Smart technology	Measures the investment and effectiveness of smart cities in ICT infrastructure, smart application diffusion, and innovative R&D.	(Abu-Rayash and Dincer, 2021; Alderete, 2020; Kairui, 2018; Ye, Chen, Li, Li and Yin, 2022)
Smart economy	Assesses the intelligence level in the city's economic structure, including the development of the smart economy, the share of innovative industries, and the impact of employment quality on residents' quality of life.	(Abu-Rayash and Dincer, 2021; Bhattacharya et al., 2020)
Smart citizen	Reflects the accumulation of human and social capital in cities, including educational attainment, talent concentration, civic engagement, and the development of lifelong learning systems.	(Alderete, 2020; Kairui, 2018; Srok et al., 2022)
Smart governance	Measures the intelligence and efficiency of government governance, covering government transparency, Service supply capacity, service responsiveness and service intelligence.	(Alderete, 2020; Bhattacharya, Bhattacharya, Mclellan and Tezuka, 2020; Yue et al., 2024)
Smart environment	Assesses the intelligence and sustainability of city's environmental management, including energy application intensity, resource recycling, pollution monitoring and the effectiveness of implementing ecological protection measures.	(Kutty et al., 2022; Suganthi, 2018; Toh, 2022)
Smart transportation	Examines the intelligence and efficiency of city's transport systems, covering the effectiveness of smart transport infrastructure, traffic optimisation and the promotion of sustainable transport modes.	(Bhattacharya, Bhattacharya, Mclellan and Tezuka, 2020)

Table 4
Area classification.

Area	Cluster	Provinces
Eastern	1	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	2	Shanxi, Anhui, Jiangxi, Henan, Huibei, Hunan
West	3	Neimenggu, Guangxi, Chongqing, Sichuan, Guizhou, Yunan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia
Northeast	4	Liaoning, Jilin, Heilongjiang

5. Result analysis

5.1. Evidence of the existence of the smart divide

The efficiency performance of the smart city system and its sub-systems in cycle t is shown in Appendix Table A2. This study uses panel data to analyze. Firstly, in order to avoid the pseudo regression problem, the stability of AI system efficiency and SC system efficiency series was tested by LLC test and IPS test. The results showed that both variables were stable series, which met the premise of causality test. The panel Granger causality test was further used to verify the causal direction of the two. In this Granger causality test, the lag order is 2. For the Granger reason that AI is not SC, P value=0.133>=0.05, so the original hypothesis is accepted, which means that AI is not the Granger reason of SC. For the Granger reason that SC is not AI, P value=0.041<0.05, so the original hypothesis is rejected, which means that AI is the Granger reason of SC. This shows that the improvement of AI system efficiency has a significant leading effect on SC system efficiency.

Secondly, pearson's test reveals a correlation coefficient between the AI system and the SC system is 0.285, which is significant at the 0.01 level (two-tailed). This indicates that the AI system and the SC system have already shown some positive correlation. In order to further intuitively present this correlation, this study grouped according to AI efficiency: for provinces with high efficiency AI (i.e. values above 0.9), the mean SC is 1. For provinces with low efficiency AI (i.e. values below 0.7), the mean SC is 0.907, which is no longer in the efficiency frontier. It can be found that AI affects SC and higher AI is accompanied by higher SC.

Fluctuations in AI trigger synchronised changes in SC. Take Hunan as an example: AI changes from 0.45(period 1)→0.54 (period 2)→0.56 (period 3)→0.61(period 4)→0.48(period 5)→0.55(period 6), and SC changes accordingly from 0.59→0.54→0.46→0.51→0.40→0.54. The overall trend of SC is highly consistent with that of AI, and SC rises in parallel with the rise of AI. SC falls back synchronously when AI falls. The situation is similar in Sichuan: AI rises from 0.61→0.67→0.51→0.67→0.49→0.41, and SC corresponds to 0.51→1.00→1.00→1.00→0.34→0.36. SC remains at a high level (1.00) during the first four periods when AI is rising or stable. In the last two periods, AI declines, and SC also dropped sharply. This further confirms the correlation between the two systems.

It can be observed that the lower the AI efficiency, the greater the difference between the efficiency of AI and SC. Provinces in the low AI region, corresponding to SC are more prone to fluctuation and inter-system divide. Observing the AISC efficiencies of provinces with low

AI regions, such as Jilin, Shaanxi, and Liaoning, it can be found that their AI efficiencies pull down their SC efficiencies and trends to a large extent. Thus, the regional differentiation brought about by AI will spread to SC and AISC, causing the gap in smart city development to widen further and creating a new smart divide. The differentiation of AISC systems is essentially the result of the technological differentiation brought about by AI and the superimposed amplification of SC.

5.2. Time-series evolution of efficiency

5.2.1 Overall efficiency

The efficiency scores are divided into three intervals: low efficiency (0-0.7), medium efficiency [0.7-0.9), and high efficiency [0.9-1]. According to Appendix Table A2, the average overall system efficiency from 2018 to 2023 was 0.86. The efficiency shows a slight downward trend, declining from 0.89 in 2018 to 0.83 in 2023. In 2019, efficiency reached a peak of 0.90, indicating that AI development and smart city construction were relatively balanced during this period. In 2020 and 2021, efficiency experienced a moderate decline, which may be attributed to the COVID-19 pandemic and the structural adjustments it triggered. In 2022 and 2023, efficiency further decreased to 0.83, suggesting that regional disparities in AI-driven smart city development may become more pronounced. This trend highlights the need for targeted policy interventions to stabilise and enhance the integration of AI within smart city systems.

There are 10 provinces with optimal efficiency levels: Beijing, Hebei, Jiangsu, Guangdong, Hainan, Henan, Neimenggu, Guangxi, Xizang, and Qinghai, which are mainly located in the eastern and western regions. The stability of Xizang, Qinghai shows strong policy implementation in China's border regions. Provinces within the low-efficiency range include Hunan, Sichuan, Hubei, Jilin, and Guizhou. Among them, Hunan consistently scores below 0.6, suggesting possible bottlenecks in resource allocation or technology implementation in its smart city system, which require particular attention.

This paper establishes a 3*3 nine-grid efficiency matrix based on the General Electric (GE) Matrix. The vertical axis represents the initial efficiency of each DMU in period t=1, while the horizontal axis reflects the trend of efficiency change from period t=1 to t=6. The initial efficiency of the vertical axis is categorised into 3 types: low, medium and high. Set the horizontal axis efficiency change trends into 3 types: decreasing, unchanged, and increasing. The dynamic efficiency change of each DMU is accurately described on 9 grids as shown in Fig. 4.

In the high-level region (Grids I, II, and IV), DMUs show higher initial efficiency and stronger positive growth trends. These are mainly concentrated in the eastern provinces. In the medium-level regions (Grids III, V, and VII), initial efficiency and growth trends move in opposite directions. Jilin and Hunan are located in Grid III with lower initial efficiency but a large growth trend. Guizhou, Liaoning, and Shanghai are located in region VII, with higher initial efficiency, but showing negative growth trends. The decline in these regions warrants attention, and measures should be taken to reverse the trend. Low-level regions (Grids VI, VIII, and IX) display low initial efficiency and slight trends over the study period. For example, Sichuan, located in Grid VI, requires greater policy focus on improving the efficiency of smart city development and advancing technological progress.

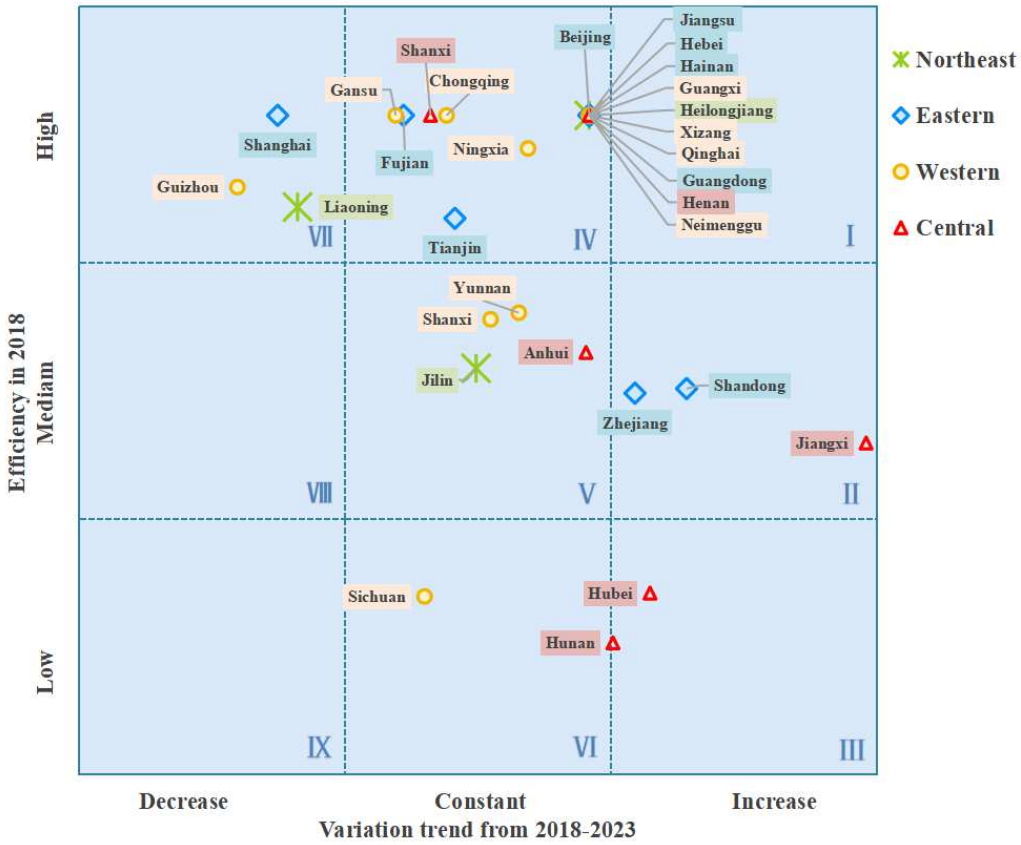


Fig. 4. Efficiency matrix.

5.2.2 Stage efficiency

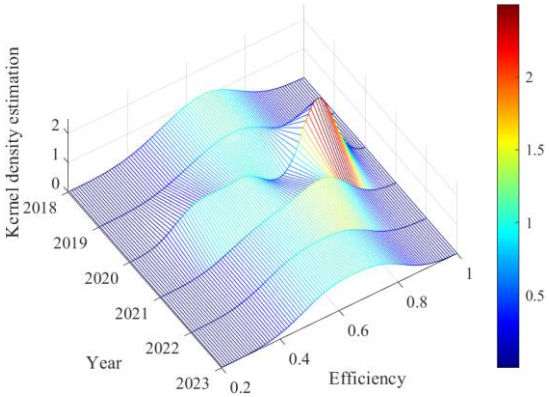
When examined by stage, the average efficiency of the AI system is 0.77, while that of the SC system is 0.96. It is clear that the SC system perform significantly better than the AI system. Investments in AI technology have constrained the overall development efficiency of smart cities and are the primary source of inefficiency. Jilin is seriously dragged down by AI, and the average efficiency of its SC system is 1, while the average efficiency of AI is only 0.36. Hunan and Sichuan's dual systems are weak, resulting in an overall efficiency of less than 0.7, which needs to be comprehensively upgraded, and it is suggested that priority should be given to solving the problem of technological inputs in AI, and then synergistically upgrading SC. Some provinces have efficiency fluctuations, such as Shanghai, where AI declines after 2021, pulling down the overall efficiency and alerting to the risk of "technological hollowing out". On the contrary, Shandong shows the catch-up effect of AI technology.

Fig. 5 presents the kernel density curves of the AI technology system and the smart city system across four regions, allowing for a visual comparison of the distribution of efficiency levels over different years. The horizontal axis indicates the range of efficiency values, the vertical axis represents the year, and the Z-axis shows the kernel density value, that is, the probability of a given efficiency level occurring.

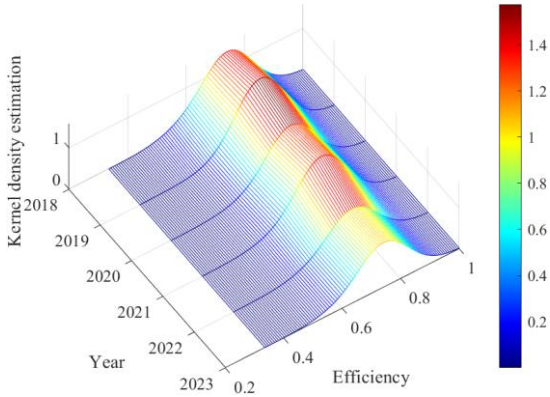
As shown in the AI stage of Fig.5(a), a clear double peak appears in 2020–2021, indicating a pronounced trend of divergence in AI technology during this period. This may be

driven by the refinement of national policies and the implementation of local pilot projects. Part of the technology continued to evolve along mature development paths, resulting in more stable and efficient outcomes. In contrast, other technologies—possibly newly emerging or based on alternative strategies—remained in the exploratory phase, with relatively low development efficiency. At the regional level, the peak in the eastern region shifts to the right, and the curve becomes narrower and steeper. This suggests that AI technology in the east performs slightly above the national average, with a relatively small inter-regional variation. The central and northeastern regions also show clear double peaks and significant fluctuations in 2020–2021, implying that development in these areas is influenced by both national policy and local industrial transformation. The generally lower efficiency in the northeast is largely due to increasing disparities in provincial-level AI system performance.

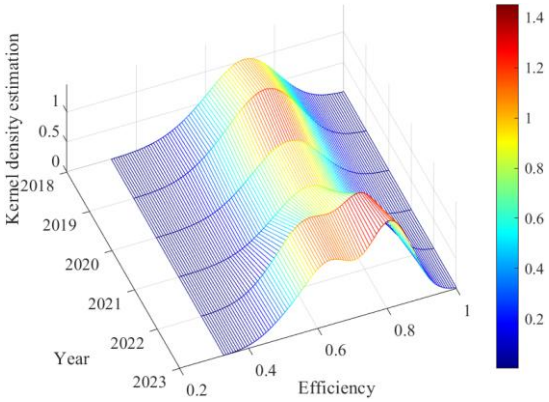
As shown in the SC stage of Fig.5(b), it always shows a single-peak pattern, with the wave peaks mainly appearing in the range of [0.7,0.8], indicating that the overall level of smart city development is relatively similar, with a small degree of dispersion. At the regional level, the kernel density surfaces for the eastern and northeastern regions lie along the horizontal axis at 1, suggesting that smart city development in these areas has approached an ideal level under the current evaluation framework. In contrast, the central and western regions pull down the overall SC efficiency, indicating greater potential for improvement in these areas.



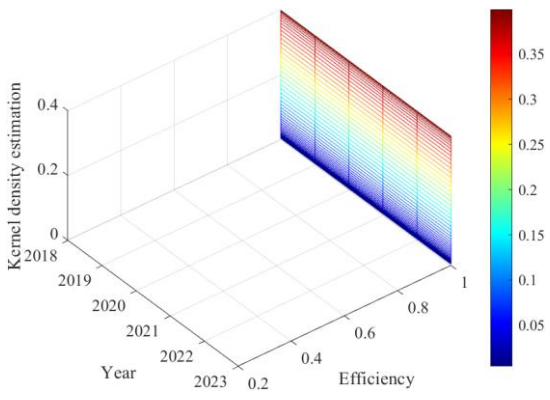
（a）AI



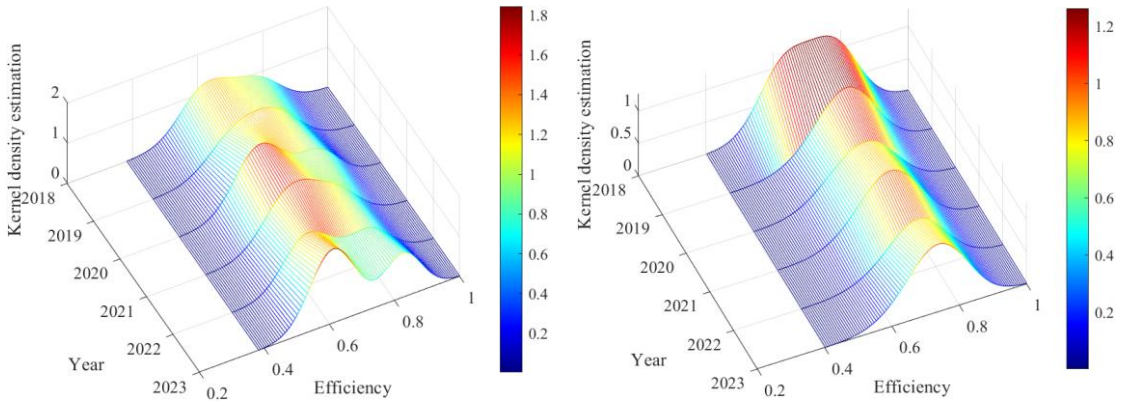
（b）SC



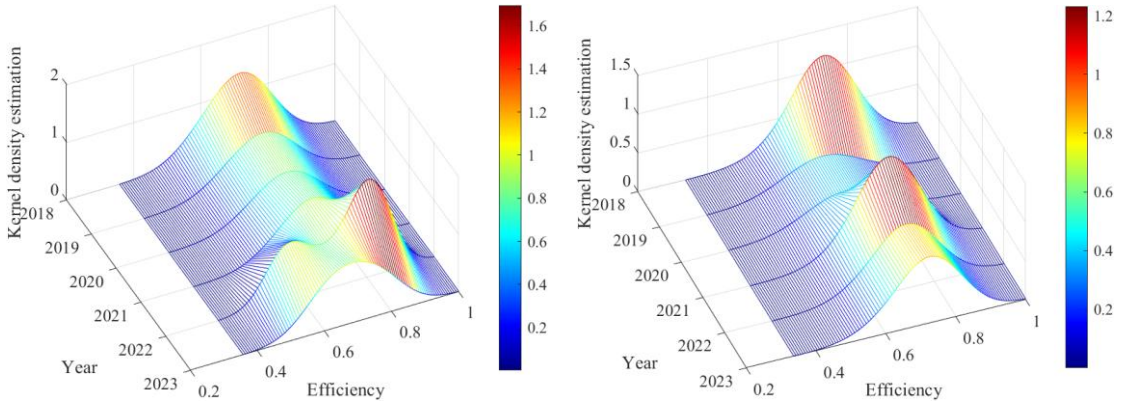
（c）AI-Eastern



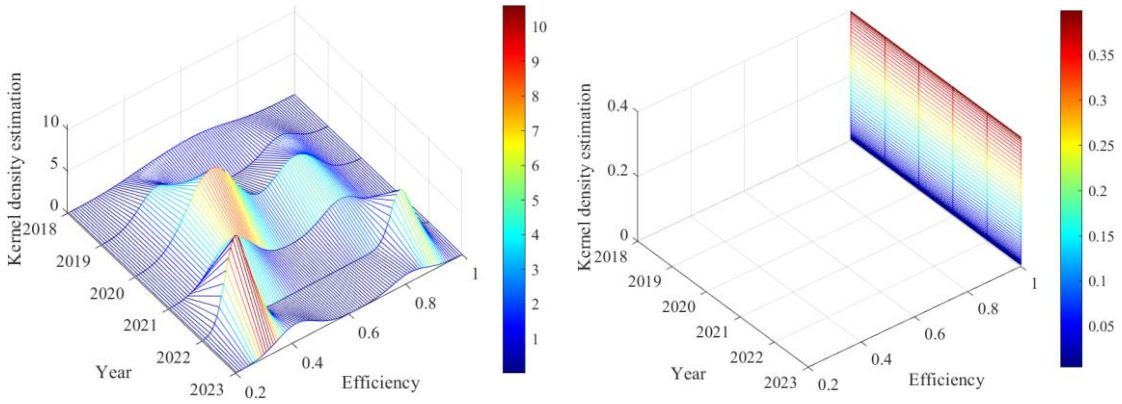
（d）SC-Eastern



（e）AI-Central　　（f）SC-Central



（g）AI-West　　（h）SC-West



（i）AI-Northeast　　（j）SC-Northeast

Fig. 5. Kernel density curve.

5.3 Spatial distribution of efficiency

In terms of regional efficiency values, the smart divide—the widening efficiency gap caused by regional imbalances in AI technology—has become evident. The eastern region has the highest average efficiency (0.92), followed by the western region (0.88), the central region (0.80), and finally the northeastern region (0.76). AI efficiency disparities have created a polarisation effect. On one hand, the eastern region maintains high stability, with high-efficiency provinces (such as Beijing and Jiangsu) having no weaknesses in their dual systems, resulting in a consistent overall efficiency of 1.0, forming a positive feedback loop. On the other hand, low-efficiency regions (such as the northeast) are trapped in a vicious

cycle of "weak foundations→insufficient investment→stagnant efficiency". The northeast region must be vigilant against the widening of the smart divide.

Fig. 6 illustrates the efficiency of smart city development across 30 Chinese provinces, with all provinces classified into five categories using the natural break classification method. Ten provinces fall into the high-efficiency category, mainly located in the Bohai Rim, the southeast coast, and the western region—namely, Beijing, Hebei, Inner Mongolia, Jiangsu, Henan, Guangdong, Guangxi, Hainan, Tibet, and Qinghai. High efficiency in economically developed regions may result from sufficient resource input, while in the western region, it is supported by policies such as the "Broadband Frontier" and "Digital Frontier", which have partially narrowed the smart divide. Notably, the distribution of medium-to-high efficiency provinces around high-efficiency provinces confirms the spatial dependence of the smart divide. For example, Fujian and Jiangxi are close to Guangdong; Shaanxi is close to Hebei. In contrast, Hubei, Hunan, Sichuan, and Guizhou provinces fail to benefit due to their distance from high-efficiency clusters. These provinces are significantly under-efficient and are continuously distributed in the central region. It is recommended that these areas prioritise the development of digital infrastructure and the upgrading of industrial structures to prevent further widening of the gap and avoid falling deeper into the smart divide.

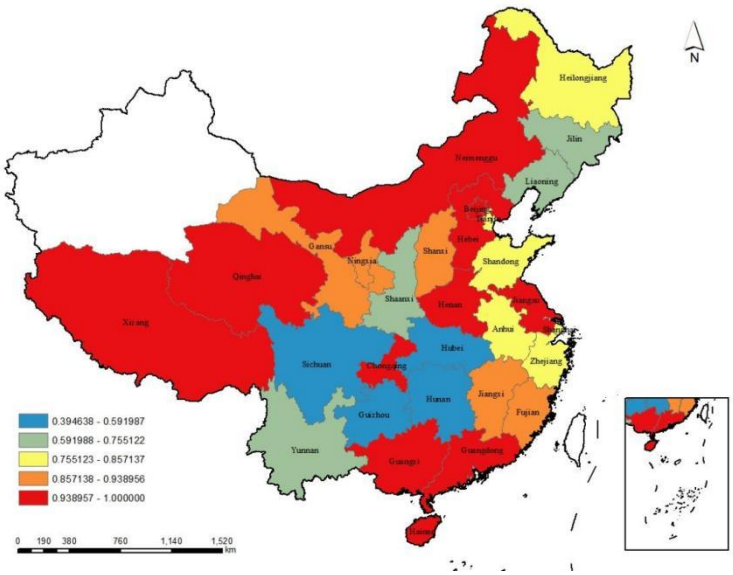
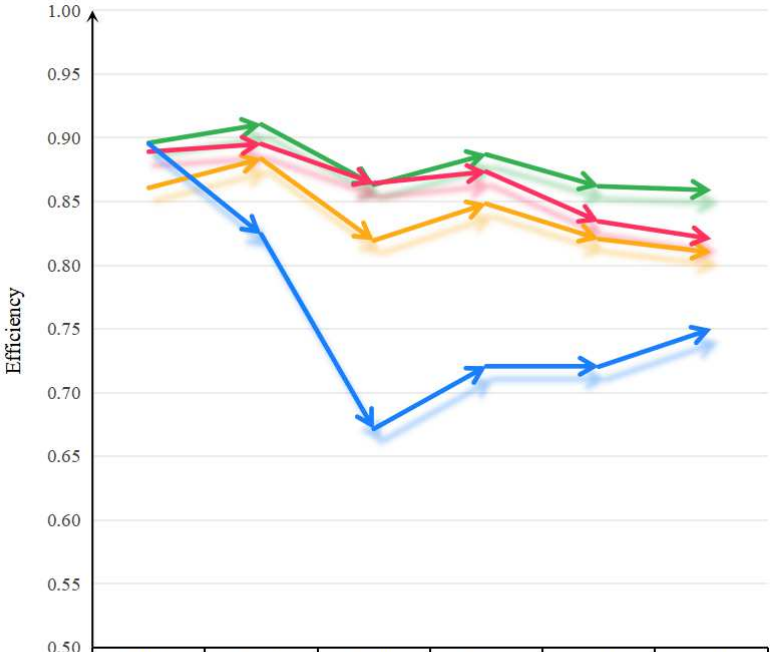


Fig. 6. Spatial distribution of efficiency.

5.4. TGR Analysis

TGR measures the technology gap between the group frontier and the meta-frontier. A TGR value closer to 1 indicates that the group's technological level is nearer to the global best-practice frontier. According to Fig. 7, the average TGR of the eastern, central, western, and northeastern regions are 0.8796, 0.8404, 0.8629, and 0.7637, respectively. This indicates that there is still a gap between the realistic technology level and the potential optimal level of each province in each region, and there is room for improvement of 12.04%, 15.96%, 13.71%, and 23.63%, respectively. The Northeast region is the most special, showing a "precipitous decline" to a "slow recovery" trend. This is related to the difficulties that the Northeast has been facing in the transformation of traditional industries, the lag in the application of new

technologies, and the continued exodus of highly skilled personnel. Possibly related to the impact of the epidemic, there is a general decline in efficiency in all regions in 2020. The East and West recover faster, reflecting greater resilience, while the Northeast recovers slowly and is still not back to 2018 levels in 2023.



	2018	2019	2020	2021	2022	2023
Eastern	0.8960	0.9105	0.8632	0.8869	0.8619	0.8589
Central	0.8607	0.8835	0.8194	0.8482	0.8206	0.8101
Western	0.8891	0.8951	0.8644	0.8734	0.8343	0.8207
Northeast	0.8954	0.8242	0.6715	0.7207	0.7204	0.7499

Fig. 7. Regional technology gap ratio in 2018-2023.

5.5 Analysis of internal key drivers

This paper evaluates the efficiency of a smart city system from an AI technology perspective, it is necessary to analyse the internal drivers of the system. Refer to Zhang et al. (2021) and Hu and Wang (2006) for evaluating energy consumption, and measuring the efficiency of variables through the ratio of target variables to actual variables. In terms of DMU, Chongqing, Sichuan, Hubei, and Hunan have the most significant impact on inefficiency in the SC stage. In terms of indicators, this paper finds that AI technology input affects the efficiency of smart city development and is the main source of inefficiency. Therefore, environmental support inputs (Id1), industrial development inputs (Id2), and research and experimental development expenditures (Id3) are taken as key indicators for analysing their impact on the overall system performance. The efficiency performance of the key indicators is shown in Appendix Table A3.

Ten provinces—Beijing, Hebei, Neimenggu, Jiangsu, Henan, Guangdong, Guangxi, Hainan, Xizang, and Qinghai (five in the east, one in the centre, and four in the west)—exhibit stable and efficient performance in key indicators. This aligns with the provinces identified as having high AISC system efficiency in the previous analysis, further validating that higher AI is associated with higher SC, and that the three key indicators of AI play a significant role. The efficiency of key indicators in Tianjin, Liaoning, and Jilin has

been declining annually, particularly in the Northeast region, reflecting challenges in regional transformation or resource depletion issues. This further explains why the AI stage efficiency in the Northeast region is relatively low. The efficiency of Id1 and Id3 is lower than that of Id2. Hubei, Jilin, Zhejiang, and Hunan have relatively low Id1 efficiency scores (0.298, 0.231, 0.383, and 0.395, respectively), while Jilin and Yunnan have consistently low efficiency scores for Id3 (0.379 and 0.395, respectively). This reflects significant shortcomings in industrial upgrading and innovation investment, necessitating policy support and resource allocation. This further explains why these provinces have lower average efficiency in the AISC system and rank lower during the study period. Furthermore, Shanghai and Liaoning experienced abrupt declines in all three key indicators, followed by sustained inefficiency, pointing to systemic challenges that local authorities must promptly address. Guizhou and Shanxi showed significant fluctuations during the study period, highlighting the presence of stage-specific shortcomings in their AI development trajectories that also warrant policy attention.

Decision-makers still have substantial room to enhance the level of AI technology across regions. Among environmental investment input indicators, the number of R&D institutions and the full-time equivalent of R&D personnel carry the greatest weight. Among industrial development input indicators, new product development funds and technical renovation funds carry the greatest weight. It can be inferred that the three key indicators are important factors influencing the efficiency of AI systems, with personnel involved in R&D and various R&D-related funds playing the most significant role. Therefore, it is recommended that local managers focus on R&D funding and R&D talent in regions experiencing efficiency fluctuations to mitigate their negative impact on AI technology.

6. Analysis of spatio-temporal divergence characteristics

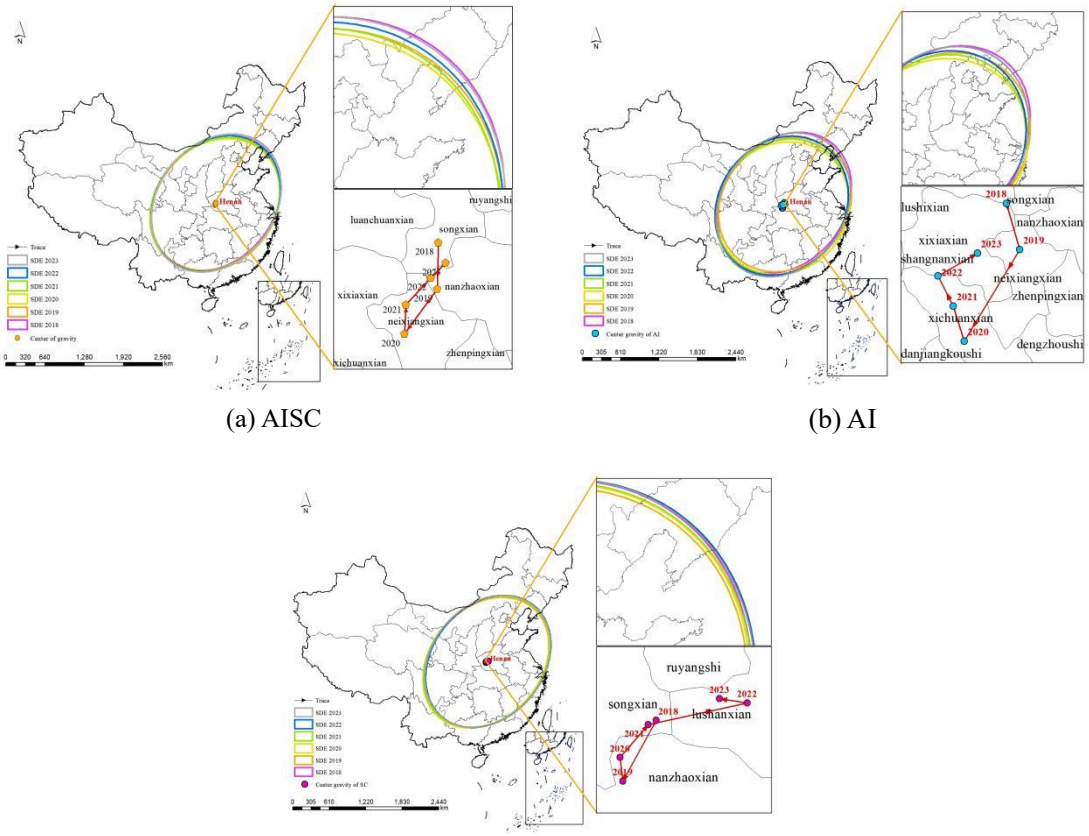
6.1 Standard deviation ellipse distribution (SDE)

The ellipse area, azimuth, and standard deviation parameters measured by the SDE model are shown in Appendix Table A4. From Fig. 8, it can be seen that the SDE has a wider distribution range, encompassing the Beijing-Tianjin-Hebei metropolitan agglomeration, the Yangtze River Delta, and the middle reaches of the Yangtze River metropolitan agglomeration, reflecting the obvious economic and social preference of the efficiency layout of the smart city. From the distribution direction, the azimuth of the SDE at different stages varies from 35.25° to 48.96°, with a general direction of "northeast - southwest".

From the AI stage, the development of AI technology in the study period has gone through the evolution process of "initial agglomeration followed by diffusion", and the ellipse area of AI stage is the smallest in 2019 (3510031.09km^2), and the largest in 2023 (3765461.31km^2), In 2020, the standard deviation ratio suddenly increased to 1.10, indicating strong directional diffusion, which once again confirmed that the rise of the AI industry in the central and western regions in that year broke the existing pattern. These findings highlight the need for policymakers to remain vigilant regarding the potential for regional imbalances and differentiation driven by the uneven development of AI technology.

From the SC stage, the ellipse area is stable at 3471769.19-3544714.59km², reflecting the balanced promotion pattern of smart city construction. The standard deviation ratio consistently remains below 1, within the narrow range of 0.761 to 0.775, suggesting an absence of significant directional bias. This spatial distribution pattern aligns well with the

policy objective of infrastructure equalisation and inclusive development.



(a) AISC (b) AI

(c) SC

Fig. 8. Standard deviation ellipse distribution.

6.2 The migration path of the centre of gravity

The migration path of the centre of gravity reveals the direction of efficiency change and the dominant region that causes such change. In this paper, the spatial migration parameters of the overall efficiency and stage efficiency during the study period are calculated, including the longitude and latitude, moving distance and direction of the centre of gravity, which are displayed in Appendix Table A4. By sequentially connecting the annual centres of gravity on a map, a visual comparison of the migration paths for overall efficiency and each stage efficiency is illustrated in Fig. 9. From a macro-geographical perspective, the centres of gravity primarily fall within the cities of Nanyang, Xuchang, and Luoyang in Henan Province. Different subsystems develop on different bases and directions, with AI favouring the south, AISC in the centre, and SC favouring the northeast.

The main moving direction of the centre of gravity during the AI stage (blue node) is "Southwest→Northwest→Northeast", with an overall shift towards the southwest. The AI gravity centre in 2020 moved significantly southwest, reflecting the beginning of the rise of the AI industry in the central and western provinces. From the policy perspective, this shift corresponds with the designation of Xi'an, Chengdu, and Chongqing as part of the “New Generation Artificial Intelligence Innovation and Development Pilot Zones” in 2020. Additionally, the “Eastern Data, Western Computing” initiative has supported the westward relocation of data centres, further promoting the development of AI infrastructure in western

regions.

The main moving direction of the centre of gravity during the SC stage (pink nodes) is "Southwest→Northwest→Northeast→Northwest", with the centre of gravity stable and biased towards the east, which aligns with the layout of the Yangtze River Delta and the Beijing-Tianjin-Hebei Smart City Pilot. The eastern region has long been the most developed area in China. The shift of the SC gravity centre to the east is the result of the combined effects of economic development, technological and policy support, and urban governance needs. This regional disparity also highlights the issue of the smart divide. In the future, central-western and northeastern regions need to adopt differentiated policy support and technological pathways to prevent the smart divide from widening and achieve balanced regional development. In 2023, the SC gravity centre shifted slightly westward, possibly reflecting that some western node cities are beginning to gain momentum. Moreover, the annual average movement of the AI gravity centre (37.18 km) is twice that of the SC gravity centre (16.89 km). This indicates that, compared to SC, AI technology is still in a period of rapid adjustment.

Comparing the AI gravity centre with the AISC gravity centre (yellow nodes), it is found that the movement trends of the two at key time points are highly compatible. In terms of the overall evolution of the trajectories, the magnitude and angle of the movement of the AI gravity centre have a potentially dominant role in the formation and development of the AISC gravity centre. Specifically, when there is a significant shift in the AI gravity centre, the AISC gravity centre quickly adjusts in response, indicating that dynamic changes in the AI system directly drive changes in the AISC gravity centre, further demonstrating the significant impact of AI on AISC. From 2022 to 2023, the AI gravity centre exhibited an eastward shift trend, not only reflecting the further concentration of technology in more developed eastern regions but also foreshadowing that the smart divide between regions may enter a phase of accelerated expansion. Managers should pay attention to this eastward shift trend, fully utilise regional economic and industrial planning, adjust spatial patterns, control regional disparities, and reduce the risk of the smart divide widening.

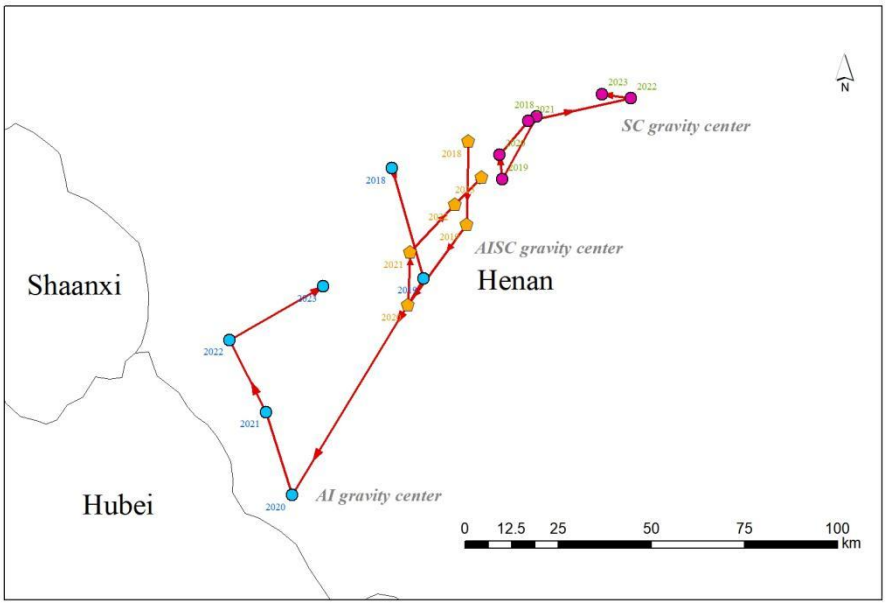


Fig. 9. Paths of AI, SC, AISC gravity centre.

7 Conclusion

7.1 Conclusion

Currently, smart city construction has entered a new AI-driven stage, and it is important to avoid the uneven regional development of AI technology to create a new "smart divide". The research of this study proves that the regional differentiation brought about by AI will spread to SC and AISC, causing the gap in smart city development to widen further and creating a new smart divide. The differentiation of AISC systems is essentially the result of the technological differentiation brought about by AI and the superimposed amplification of SC. Specifically, the average overall efficiency of smart cities in 30 provinces is 0.86 from 2019 to 2023. AI technology limits the efficiency of smart city development and is the main source of inefficiency. R&D funding and R&D talent are major drags on AI technology improvement. In order to improve the overall efficiency of smart cities, policymakers need to focus on improving the performance of the AI systems in Jilin**,** Zhejiang, and Hubei, while stopping the continued decline in efficiency in Tianjin and Liaoning, and focusing on the SC systems in Chongqing and Hubei. Hunan and Sichuan are facing dual systems and dual lows, and need to prioritise the issue of AI technology investment before coordinating the upgrade of SC. The overall low efficiency in the Northeast region is due to the widening provincial differences in the efficiency of the AI system. The SC efficiency is dragged down by the central and western regions, which have significant room for improvement.

From the SDE parameter, it can be observed that the efficiency of different stages of the spatial distribution of the "biased northeast - biased southwest" direction. The development of AI technology has gone through an evolutionary process of "initial agglomeration followed by diffusion". The construction of the smart city stage is in a balanced promotion mode. From the migration path of gravity centre, it can be seen that by 2020, the AI industry in the central and western provinces began to rise, while the SC system's centre of gravity remained stable and biased towards the east. From the overall evolution of the trajectory, the AI gravity centre has a potentially dominant role in the formation and development of the AISC gravity centre. In 2022-2023, the AI gravity centre shows a trend of eastward shift, which signals that the inter-regional smart divide may enter an accelerated stage of expansion. The AISC system is currently undergoing developmental adjustments in terms of regional spatial distribution. Managers should leverage regional economic strategies, industrial planning, and other relevant policies to mitigate the widening of the smart divide. Reducing the regional economic development gap and addressing the spatial imbalances caused by AI technology is crucial for consolidating the effectiveness of smart city development.

7.2 Policy Recommendations

Enhancing the development potential of AI technology driven by scientific innovation is crucial. This paper finds that key indicators within AI technology are a significant source of inefficiency in smart cities. To solidify the development impact of smart cities, it is necessary to increase investment in AI R&D and attract more R&D talent. Drawing lessons from Shanghai, it is essential to avoid technological discontinuities. Strengthening the coordinated development of AI technology across regions is also critical.

Formulating differentiated regional strategies is essential. The policy objectives should focus on consolidating the advantages of SC while optimising the transformation of AI

technology. For the eastern region, the emphasis should be on advancing core technological breakthroughs and establishing a technology export mechanism. For the central region, leveraging its position as a "transitional zone" is crucial. This could involve creating regional technology innovation alliances to make up for technical shortcomings. The suggestion for the western region is to make use of the policy dividend to promote dual-system synergy. At the same time, cultivate local digital economy enterprises. For the northeastern region, which faces challenges such as technological discontinuity, talent outflow, and insufficient investment, a dedicated revitalisation fund should be established, along with a talent repatriation programme to prevent the creation of a "technological depression". Furthermore, to avoid a blind pursuit of cutting-edge technologies like large-scale models, the focus should be on "AI + heavy industry" to ensure complementary, rather than competing, development.

Block the continued widening of the smart divide. A dynamic monitoring system should be established at the national level, and a "Smart Gap Index" should be issued and incorporated into regional development assessments. Simultaneously, the focus should be on "filling shortcomings" and "preventing excess", such as focusing on basic access in the central and western parts of the country and avoiding technology bubbles in the eastern part of the country. Dovetailing AI technology and smart city construction development planning. Avoid the emergence of local governments due to the pursuit of performance, independently carried out the construction of smart modules, resulting in a waste of resources.

The smart city of the future should put "citizen" at the core, rather than being an appendage of technology. Through the effective services and guidance of the city government, it is necessary to give full play to the subjective role of urban residents, so that they can become the centre of the city.

References

Abu-Rayash, A. and Dincer, I., 2021, "Development of Integrated Sustainability Performance Indicators for Better Management of Smart Cities", *Sustainable Cities and Society*, 67: 102704.

Acemoglu, D. and Restrepo, P., 2021, "Automation and New Tasks: How Technology Displaces and Reinstates Labor", *Operations Research: Management Science*, (5/6): 61.

Aditya, T., Ningrum, S., Nurasa, H. and Irawati, I., 2023, "Community Needs for the Digital Divide On the Smart City Policy", *Heliyon*, 9(8): 15.

Ahvenniemi, H., Huovila, A., Pinto-Sepp, I. and Airaksinen, M., 2017, "What are the Differences Between Sustainable and Smart Cities?", *Cities*, 60(part_PA): 234-245.

Alahi, M. E. E., Sukkuea, A., Tina, F. W., Nag, A., Kurdthongmee, W., Suwannarat, K. and Mukhopadhyay, S. C., 2023, "Integration of Iot-Enabled Technologies and Artificial Intelligence (Ai) for Smart City Scenario: Recent Advancements and Future Trends", *Sensors (14248220)*, 23(11).

Alderete, M. V., 2020, "Exploring the Smart City Indexes and the Role of Macro Factors for Measuring Cities Smartness", *Social Indicators Research*, 147(2): 567-589.

Allam, Z. and Dhunny, Z. A., 2019, "On Big Data, Artificial Intelligence and Smart Cities", *Cities*, 89: 80-91.

Allam, Z. and Jones, D. S., 2020, "On the Coronavirus (Covid-19) Outbreak and the Smart City Network: Universal Data Sharing Standards Coupled with Artificial Intelligence (Ai) to Benefit Urban Health Monitoring and Management", *Healthcare*, 8(1): 46.

Alsubai, S., Dutta, A. K., Alghayadh, F., Alamer, B. H., Pattanayak, R. M., Ramesh, J. V. N. and

Mohanty, S. N., 2024, "Design of Artificial Intelligence Driven Crowd Density Analysis for Sustainable Smart Cities", *Ieee Access*, 12: 121983-121993.

Bhattacharya, T. R., Bhattacharya, A., Mclellan, B. and Tezuka, T., 2020, "Sustainable Smart City Development Framework for Developing Countries", *Urban Research and Practice*, 13(2): 180-212.

Bokhari, S. A. A. and Myeong, S., 2023, "The Impact of Ai Applications On Smart Decision-Making in Smart Cities as Mediated by the Internet of Things and Smart Governance", *Ieee Access*, 11: 120827-120844.

Braun, T., Fung, B. C. M., Iqbal, F. and Shah, B., 2018, "Security and Privacy Challenges in Smart Cities", *Sustainable Cities and Society*, 39: 499-507.

Caragliu, A. and Del Bo, C. F., 2023, "Smart Cities and the Urban Digital Divide", *Npj Urban Sustainability*, 3(1): 43.

Chao, L., Ruo-Yu, F. U., Jia-Hui, L. I. and Wen-Wen, Z., 2019, "Research Into Financing Efficiency of Artificial Intelligence Industry Based On Dea-Tobit Method", *Operations Research and Management Science*, 28(6): 144-152.

Chen, G. and Zhang, J., 2022, "Applying Artificial Intelligence and Deep Belief Network to Predict Traffic Congestion Evacuation Performance in Smart Cities", *Applied Soft Computing*, 121: 108692.

Chen, H., Deng, K. and Schneider, F., 2024, "Does City Smartness Improve Equality? Research On the Impact of Smart City Construction On Income Inequality", *Pacific Economic Review*, 29(3): 328-353.

Costa, D. G., 2024, "Resilient Smart Cities for Everyone: Overcoming Inequalities in Emergency Solutions", *Technology & Society Magazine, Ieee*, 43(4): 97-104.

Cui, L. and Yang, K., 2018, "Construction of Evaluation Indicator System for Smart Cities", *Statistics and Decision*, 34(06): 33-38.(In Chinese).

El Ghati, O., Alaoui-Fdili, O., Chahbouni, O., Alioua, N. and Bouarifi, W., 2024, "Artificial Intelligence-Powered Visual Internet of Things in Smart Cities: A Comprehensive Review", *Sustainable Computing-Informatics & Systems*, 43: 101004.

Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., Hamza, E. H., Rooney, D. W. and Yap, P. S., 2023, "Artificial Intelligence for Waste Management in Smart Cities: A Review", *Environmental Chemistry Letters*, 21(4): 1959-1989.

Fang, W. and Xu, Z., 2022, "Smart Cities: Connotation Reconstruction, Major Dilemmas, and Optimisation Approaches", *Southeast Academic Journal*, 84-94.(In Chinese).

Guo, Z., 2024, "Application Process of Artificial Intelligence in Smart Cities", *Automation and Instrumentation*, 39(09): 162-164.(In Chinese).

Hammerschmidt, T., Stolz, K. and Posegga, O., 2025, "Bridging the Gap: Inequalities that Divide those Who Can and Cannot Create Sustainable Outcomes with Ai", *Behaviour & Information Technology*, 5: 1-30.

Harrison, C., Eckman, B., Hamilton, R., Hartswick, P. and Williams, P., 2010, "Foundations for Smarter Cities", *Ibm Journal of Research and Development*, 54(4): 1-16.

Hu, J. L. and Wang, S. C., 2006, "Total-Factor Energy Efficiency of Regions in China", *Energy Policy*, 34(17): 3206-3217.

Jaramillo-Alcazar, A., Govea, J. and Villegas-Ch, W., 2023, "Advances in the Optimization of Vehicular Traffic in Smart Cities: Integration of Blockchain and Computer Vision for Sustainable Mobility", *Sustainability*, 15(22): 15736.

Kairui, Y., 2018, "Intelligent Evaluation Approach for Smart City Based On Dea Model: Taking

Wuhan, China as an Example", *Journal of Intelligent and Fuzzy Systems*, 35(3): 2667-2677.

Kocisova, M., Filo, M., Kadarova, J. and Suhanyiova, A., 2024, "Integrating Bsc-Dea Approach and Artificial Intelligence in Innovation Management", *Mm Science Journal*.

Kourtit, K., Nijkamp, P. and Suzuki, S., 2021, "Comparative Urban Performance Assessment of Safe Cities through Data Envelopment Analysis", *Regional Science Policy and Practice*, 13(3): 591-603.

Kourtit, K., Nijkamp, P. and Suzuki, S., 2023, "Quantitative Performance Assessment of Asian Stellar Cities by a Dea Cascade System: A Capability Interpretation", *The Annals of Regional Science*, 70(1): 259-286.

Kutty, A. A., Kucukvar, M., Abdella, G. M., Bulak, M. E. and Onat, N. C., 2022, "Sustainability Performance of European Smart Cities: A Novel Dea Approach with Double Frontiers", *Sustainable Cities and Society*, 81: 103777.

Li, G., Luan, T. H., Li, X., Zheng, J., Lai, C., Su, Z. and Zhang, K., 2024, "Breaking Down Data Sharing Barrier of Smart City: A Digital Twin Approach", *Ieee Network*, 38(1): 238-246.

Li, X., Wang, Q. and Tang, Y., 2024, "The Impact of Artificial Intelligence Development On Urban Energy Efficiency—Based On the Perspective of Smart City Policy", *Sustainability*, 16(8): 3200.

Lifelo, Z., Ding, J., Ning, H. and Dhelim, S., 2024, "Artificial Intelligence-Enabled Metaverse for Sustainable Smart Cities: Technologies, Applications, Challenges, and Future Directions", *Electronics*, 13(24): 4874.

Ling, X., Luo, Z., Feng, Y., Liu, X. and Gao, Y., 2023, "How Does Digital Transformation Relieve the Employment Pressure in China? Empirical Evidence From the National Smart City Pilot Policy", *Humanities and Social Sciences Communications*, 10(1): 617.

Liu, H., 2024, "Preliminary Exploration of Urban Evaluation Methodology", *Geographical Research*, 43(03): 596-620.(In Chinese).

Liu, J., Chang, H., Forrest, Y. L. and Yang, B., 2020, "Influence of Artificial Intelligence On Technological Innovation: Evidence From the Panel Data of China's Manufacturing Sectors", *Technological Forecasting and Social Change*, 158: 120142.

Liu, W., Xu, Y., Fan, D., Li, Y. and Zheng, J., 2021, "Alleviating Corporate Environmental Pollution Threats Toward Public Health and Safety: The Role of Smart City and Artificial Intelligence", *Safety Science*, 143: 105433.

Lombardi, P., Giordano, S., Farouh, H. and Yousef, W., 2012, "Modelling the Smart City Performance", *Innovation the European Journal of Social Science Research*, 25(2): 137-149.

Lu, J., Huang, X., Chen, Y. and Xiao, X., 2013, "Spatiotemporal Evolution of Provincial Carbon Footprints in China Based On Energy Consumption", *Geographical Research*, 32(02): 326-336.(In Chinese).

Luo, Q., Zhuang, Y., Gu, X. and Lina, Z., 2022, "Heterogeneous Environmental Regulation Effects On China's Green Technological Innovation Efficiency and Spatiotemporal Transitions", *Science and Technology Progress and Policy*, 39(14): 52-62.(In Chinese).

Manman, L., Goswami, P., Mukherjee, P., Mukherjee, A., Yang, L., Ghosh, U., Menon, V. G., Qi, Y. and Nkenyereye, L., 2021, "Distributed Artificial Intelligence Empowered Sustainable Cognitive Radio Sensor Networks: A Smart City On-Demand Perspective", *Sustainable Cities and Society*, 75: 103265.

Mao, F., Gao, Y. and Zhou, C., 2022, "Spatial Pattern Evolution and Driving Factors of the Digital Industry in the Yangtze River Economic Belt", *Geographical Research*, 41(06): 1593-1609.(In Chinese).

Molnar, A., 2021, "Smart Cities Education: An Insight Into Existing Drawbacks", *Telematics and Informatics*, 57(1): 101509.

O'Donnell, C., Rao, D. and Battese, G., 2008, "Metafrontier Frameworks for the Study of Firm-Level Efficiencies and Technology Ratios", *Empirical Economics*, 34(2): 231-255.

Preston, S., Mazhar, M. U. and Bull, R., 2020, "Citizen Engagement for Co-Creating Low Carbon Smart Cities: Practical Lessons From Nottingham City Council in the Uk", *Energies*, 13.

Qian, Y., Yuan, R. and Li, Y., 2025, "Measurement of Smart City Resilience and Dynamic Evolution", *Frontiers in Engineering Management Science*, 44(02): 41-48.(In Chinese).

Ringenson, T., Eriksson, E., Rivera, M. B. and Wangel, J., 2017, "The Limits of the Smart Sustainable City", 3-9.

Shahrabani, M. M. N. and Apanaviciene, R., 2024, "An Ai-Based Evaluation Framework for Smart Building Integration Into Smart City", *Sustainability*, 16: 8032.

Shannon, C. E., 1948, "A Mathematical Theory of Communication", *The Bell System Technical Journal*, 27(3): 379-423.

Shu, Y., Deng, N., Bie, A., Wu, Y. and Bao, S., 2024, "Unlocking the Role of Smart Cities in Technological Innovation: Evidence From China", *Applied Economics*, 56(58): 273-8287.

Singh, S., Sharma, P. K., Yoon, B., Shojafar, M., Cho, G. H. and Ra, I. H., 2020, "Convergence of Blockchain and Artificial Intelligence in Iot Network for the Sustainable Smart City - Sciencedirect", *Sustainable Cities and Society*, 63: 102364.

Skubis, I., Wolniak, R. and Grebski, W. W., 2024, "Ai and Human-Centric Approach in Smart Cities Management: Case Studies From Silesian and Lesser Poland Voivodships", *Sustainability*, 16(18): 8279.

Song, D., Li, C. and Xiangyou, L., 2021, "Does New Infrastructure Construction Promote 'Quantity and Quality Improvement' in Green Technological Innovation? Evidence From National Smart City Pilot Programs", *China Population, Resources and Environment*, 31(11): 155-164.(In Chinese).

Song, M., Tan, K. H., Wang, J. and Shen, Z., 2022, "Modeling and Evaluating the Economic and Ecological Operation Efficiency of Smart City Pilots", *Cities*, 124(3): 103575.

Srok, A., Antoni, J. J. and Borkovi, M., 2022, "Being an Efficient Smart City in Croatia: The View of Citizens", *Lex Localis*, 20(4): 959-988.

Su, H., Qu, X., Tian, S., Ma, Q., Li, L. and Chen, Y., 2022, "Artificial Intelligence Empowerment: The Impact of Research and Development Investment On Green Radical Innovation in High-Tech Enterprises", *Systems Research and Behavioral Science*, 39(3): 489-502.

Suganthi, L., 2018, "Multi Expert and Multi Criteria Evaluation of Sectoral Investments for Sustainable Development: An Integrated Fuzzy Ahp, Vikor / Dea Methodology", *Sustainable Cities and Society*, 43: 144-156.

Toh, C., 2022, "Smart City Indexes, Criteria, Indicators and Rankings: An in-Depth Investigation and Analysis", *Iet Smart Cities*, 4(3): 211-228.

Tone, K., 2001, "A Slacks-Based Measure of Efficiency in Data Envelopment Analysis", *European Journal of Operational Research*, 130(3): 498-509.

Tone, K. and Tsutsui, M., 2009, "Network Dea: A Slacks-Based Measure Approach", *European Journal of Operational Research*, 197(1): 243-252.

Tone, K. and Tsutsui, M., 2014, "Dynamic Dea with Network Structure: A Slacks-Based Measure Approach", *Omega*, 42(1): 124-131.

Ullah, Z., Al-Turjman, F., Mostarda, L. and Gagliardi, R., 2020, "Applications of Artificial Intelligence and Machine Learning in Smart Cities", *Computer Communications*, 154: 313-323.

Vanolo, A., 2014, "Smartmentality: The Smart City as Disciplinary Strategy", *Urban Studies*, 51(5): 883-898.

Wan, A. and Cui, W., 2025, "Has the Green Total Factor Productivity Increased in the Early Stage of the Establishment of Smart City", *Plos One*, 20(5): 322922.

Wang, S. and Zheng, L., 2013, "Comparison of Smart City Evaluation Indicator Systems at Home and Abroad", *E-Government*, (01): 92-100.(In Chinese).

Wojewnik-Filipkowska, A., Gierusz, A. and Krauze-Malankowska, P., 2024, "Fundamental Power of City – a Proposition of a New Paradigm and Index for City Development", *Cities*, 144: 104630.

Wu, X. and Yang, Z., 2010, "Smart City Concept and Future Urban Development", *Urban Development Studies*, 17(11): 56-60.(In Chinese).

Xia, X., Yu, R. and Zhang, S., 2023, "Evaluating the Impact of Smart City Policy On Carbon Emission Efficiency", *Land*, 12(7): 1292.

Xu, C. and Lin, B., 2025, "Embracing Artificial Intelligence: How Does Intelligent Transformation Affect the Technological Innovation of New Energy Enterprises?", *Ieee Transactions On Engineering Management*, 72: 703-716.

Yan, Z., Jiang, L., Huang, X., Zhang, L. and Zhou, X., 2023, "Intelligent Urbanism with Artificial Intelligence in Shaping Tomorrow's Smart Cities: Current Developments, Trends, and Future Directions", *Journal of Cloud Computing*, 12(1): 179.

Ye, F., Chen, Y., Li, L., Li, Y. and Yin, Y., 2022, "Multi-Criteria Decision-Making Models for Smart City Ranking: Evidence From the Pearl River Delta Region, China", *Cities*, (128): 103793.

Yigitcanlar, T., Desouza, K. C., Butler, L. and Roozkhosh, F., 2020, "Contributions and Risks of Artificial Intelligence (Ai) in Building Smarter Cities: Insights From a Systematic Review of the Literature", *Energies*, 13(6): 1473.

Yue, A., Mao, C., Wang, Z., Peng, W. and Zhao, S., 2024, "Finding the Pioneers of China's Smart Cities: From the Perspective of Construction Efficiency and Construction Performance", *Technological Forecasting and Social Change*, 204: 12341.

Zhang, L., Zhuang, Y., Chiu, Y. H., Pang, Q., Chen, Z. and Shi, Z., 2021, "Measuring Urban Integrated Water Use Efficiency and Spatial Migration Path in China: A Dynamic Two-Stage Recycling Model within the Directional Distance Function", *Journal of Environmental Management*, 298(15): 113379.

Zhang, Y., Geng, P., Sivaparthipan, C. B. and Muthu, B., 2021, "Big Data and Artificial Intelligence Based Early Risk Warning System of Fire Hazard for Smart Cities", *Sustainable Energy Technologies and Assessments*, 45: 100986.

Zhang, Z. and Deng, F., 2023, "How Can Artificial Intelligence Boost Firms' Exports? Evidence From China", *Plos One*, 18(8).

Zheng, Z. and Sieber, R., 2021, "Putting Humans Back in the Loop of Machine Learning in Canadian Smart Cities", *Transactions in Gis*, 26(1): 8-24.

Zhou, Y., An, Y., Qin, L., Quan, K. and Han, X., 2025, "Empowering Smart Cities and Urban Digital Transformation with 'Ai + Big Data'", *Intelligent Buildings and Smart Cities*, (04): 6-10.(In Chinese).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix.docx
- titlepage3.docx