Heliyon 10 (2024) e26245

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Empirical analysis of factors influencing industrial eco-efficiency in the Yellow River Basin from a social embeddedness perspective

Junjie Wang [a], Zhun Chen [b,*], Taizheng Chen [a], Wei Wang [c], Bailu Liu [a]

[a] The College of Geography and Environmental Science, Henan University, Kaifeng, 475000, China
[b] School of Philosophy and Public Management, Henan University, Kaifeng, 475000, China
[c] School of Culture and Tourism, Henan University, Kaifeng, 475000, China

ARTICLE INFO

Keywords:
Industrial eco-efficiency
Social embeddedness
Yellow River Basin
Hierarchical linear modeling

ABSTRACT

Measuring industrial eco-efficiency (IEE) is essential to improve environmental quality and industrial restructuring. However, most studies ignore the influence of embeddedness on industrial eco-efficiency and lack analysis of the pathways of influence factors. Therefore, this study assesses industrial eco-efficiency in the Yellow River Basin (YRB) using a super-efficiency model slacks-based measure (Super-SBM) that considers non-desired outputs, outlines the social embeddedness of IEE, and empirically analyzes the driving mechanism of IEE from the perspective of embeddedness by constructing hierarchical linear modeling (HLM) to address the pathways of action of the influencing factors of industrial eco-efficiency. The results showed that 50.79% of the overall differences in IEE in the YRB were caused by social embeddedness. Economic development level, industrial agglomeration, and environmental regulation (ER) are significant direct influencing factors. Increasing cognitive and cultural embeddedness will enhance the positive relationship between economic development level and IEE. Political and relational embeddedness significantly moderates the positive relationship between industrial agglomeration and eco-efficiency. Cultural embeddedness can significantly and directly affect industrial eco-efficiency and weaken the positive relationship between ERs and industrial eco-efficiency. Therefore, improving IEE should consider both fundamental and embedded factors. Our findings are conducive to promoting high-quality development in the YRB and support the government in formulating differentiated policies. In addition, this paper tries to establish an empirical analysis method suitable for social embeddedness theory, and the empirical results help to improve the situation due to the lack of empirical analysis of social embeddedness theory.

Junjie Wang (1998-), male, from Fengqiu, Henan Province, master's degree student, research interests are environmental science and regional development; Zhun Chen (1988-), male, from Lushan, Henan Province, doctor of management, associate professor, research interests are environmental science and natural resources management (**corresponding author**); Taizheng Chen (1962-), male, native of Lushan, Henan Province, is a professor and supervisor of doctoral students with research interests in environmental science and regional development; Wei Wang (1990-), male, native of Neihuang, Henan Province, is an associate professor and supervisor of master students, with research interests in rural geography and rural revitalization; Bailu Liu (1999-), male, native of Xinye, Henan Province, is a master student, with research interests in resource and environmental science.

* Corresponding author.
E-mail address: zhunchen@henu.edu.cn (Z. Chen).

https://doi.org/10.1016/j.heliyon.2024.e26245
Received 10 August 2023; Received in revised form 20 January 2024; Accepted 8 February 2024
Available online 16 February 2024

1. Introduction

Industry is the cornerstone of economic growth and plays an irreplaceable role in the development of national economies. In 2022, China's industrial-added value exceeded 40 trillion dollars, accounting for 33.2% of the national GDP [1]. Industry involves a large number of industrial chains and is an essential sector of material creation. While its existence also effectively solves the problem of employment, and its development has a significant impact on the macroeconomy. Over the past 40 years since the reform and opening up, China's industry has developed dramatically. However, with the deepening of China's industrialization process, the dependence of national economic growth on non-renewable resources has deepened [2], and the industry itself is characterized by high energy consumption and high pollutant emissions, resulting in increasing pollutant emissions from resource consumption. Therefore, promoting the harmonious development of industry and the ecological environment is the key to constructing ecological civilization in China.

As a significant ecological barrier and energy and heavy industrialization base in China, the Yellow River Basin (YRB) has a unique strategic position as China's potential for upgrading the national development level. With the development of the times, the Yellow River Basin's economic and social development and ecological environment needs have become increasingly intense, and the backwardness of the development process, such as low technology content and crude production mode, has emerged endlessly. Along both sides of the Yellow River, energy and chemical industries, iron and steel smelting, food processing, and other highly polluting industries are concentrated in the layout. At the same time, the level of pollution control, environmental management, and risk prevention and control is relatively backward [3]. Some enterprises still have problems, such as exceeding the standard emissions and illegal emissions. According to statistics, at the end of 2017, sewage discharge in the YRB reached 44.94 million tons [4]; at the end of 2019, significant tributaries with less than V-level water quality accounted for 16.21% of the total length of the basin [5], industrial discharge is the main source of pollution in the YRB [6]. The ecological and environmental problems caused by industrial development have restricted the construction of ecological civilization in the YRB [7].

In view of this, the State Council issued the Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin in 2021, which provides strong support for the high-quality development of the YRB and further highlights the critical position of the YRB in national development [8]. The development mode of the YRB is currently in a critical period of transformation, and its economic structure is being optimized. Promoting green industrial development and avoiding over-exploitation is the way in guiding the YRB from industrial to ecological civilization. Most existing scholars believe that IEE can effectively measure industrial development and environmental protection and is an important basis for measuring the level of green development [9]. In this context, scientific evaluation of the industrial eco-efficiency of the YRB, analysis of the influence mechanism of the driving factors, and formulation of pollution reduction policies are of great significance for improving the IEE of the YRB and of great practical significance for realizing the high-quality development of the YRB.

The concept of eco-efficiency was first introduced in the 1990s to measure the environmental performance of economic activities [10], with the core idea of maximizing economic profits with minimal resource and environmental inputs. With the in-depth exploration of sustainable development theories worldwide, IEE has become an important subject of research. In terms of measurement methods, the more widely used method is data envelopment analysis (DEA) [11]. Among the traditional DEA models, the CCR and BCC models have garnered attention for their relatively practical evaluation of DMU units. Some scholars have evaluated the industrial eco-efficiency of 30 provinces in China using the CCR [12] model and the BBC [13] model, respectively, proving the usability and practicality of the models. However, the models above cannot effectively control the increase in "unwanted output." Researchers have progressively begun to employ enhanced DEA models, such as the two-phase DEA model [11] and three-phase DEA model [14], to better account for environmental pollution factors in the output system and to obtain a more realistic IEE. In addition, Dai et al. measured the industrial eco-efficiency (IEE) of seven provinces in East China through the super-efficiency DEA method [15]. In summary, the DEA method can evaluate IEE scientifically and effectively, but some studies lacked in-depth analysis of the factors influencing IEE.

Exploring the factors influencing efficacy can provide a scientific foundation and decision-making basis for implementing government or business strategies. Existing studies have focused on the following factors: (1) The level of economic development, whereby the improvement of economic level has led to technological progress, and industrial eco-efficiency has increased [16]. On the contrary, as the economy continues to grow, it further exacerbates environmental pollution [17], which is not conducive to the improvement of IEE. (2) The intensity of industrial agglomeration, industrial structure and environmental regulations all have positive effects on IEE. The positive externalities formed by industrial agglomeration and the optimization and adjustment of industrial structure are all conducive to the rational allocation of resources and bring about an increase in efficiency; the increase in environmental regulations raises the threshold of industrial entry and stimulates the enthusiasm of enterprises to innovate, thus improving the economy and the environment [18–20]. (3) Foreign capital utilization. Foreign enterprises will bring advanced technology and experience, which is conducive to efficiency [21]. However, some studies suggest that some foreign enterprises are oriented towards lax environmental policies, which aggravate environmental pollution and are not conducive to efficiency [22].

In recent years, scholars have evaluated IEE at different scales from the macro level of the country, provinces, cities, and urban agglomerations and the micro level of industrial enterprises. In addition, the YRB, a significant ecological barrier and economic zone in China [23], has been a hot research area in academia. Xu et al. assessed the relationship between environmental regulations and green innovation efficiency in the YRB by adopting a panel threshold model, and the results show that the intensity of the impact of environmental regulations is different between different regions [24]; Song et al. explored the spatial and temporal evolution of IRR and the influencing factors in the YRB by setting up a panel regression model. The study shows significant spatial autocorrelation of the IEE, and the influencing factors of the IEE are spatially heterogeneous [25]; Ren et al. predicted the relationship between economic growth, industrial development and ecological environment in the YRB and concluded that the coupling between the three is seriously out of order [26]; Wang et al. measured the green eco-efficiency of 43 prefectural-level cities in the YRB, and the results showed that there are differences in the impact of industrial structure on efficiency among different cities [27].

To summarize, the existing research on IEE has achieved rich results and formed a relatively perfect research system, but there is still room for expansion. On the one hand, relevant research focuses on qualitatively evaluating influencing factors. It lacks the analysis of the paths of the influencing factors of IEE, which can provide a theoretical basis for the improvement of IEE and the formulation of relevant policies; On the other hand, although some studies have also considered factors such as foreign trade and government support, they focus on the impact of economic factors on resources and environment and lack of "embeddedness" thinking and attention to social network structure and social culture. According to Granovetter, "The organizations and their behaviors are subject to social relations, and it is a severe misunderstanding to treat them as independent individuals [28]." Based on this, we adopt the Super-SBM model to measure the IEE of 61 prefecture-level cities in the YRB from 2006 to 2019; we construct a hierarchical linear modeling to empirically analyze the influencing factors of IEE under the embeddedness perspective. The specific objectives are (1) to construct an empirical analysis framework of the influencing factors of IEE and generalize the social embeddedness of IEE; (2) to explore the influence of embeddedness factors on IEE and reveal the mechanism of the influencing factors; (3) to clarify the direction and focus of improving IEE in the YRB; and to put forward countermeasures and suggestions for optimizing the coordinated development of industry and ecology in the YRB. This study aims to answer the following two key questions: (1) What kind of embeddedness of IEE influencing factors is there, and how does embeddedness affect IEE? (2) What kind of path mechanism influences IEE factors?

By bringing in the above issues, this study fills the gap in the literature in the following two aspects. Firstly, it cuts in from the dimension of social scenario factors and emphasizes the role of embedded factors in improving IEE, which makes up for the lack of current research on the embeddedness of IEE; moreover, on the basis of existing research, it comprehensively considers the fundamental factors and embeddedness factors, constructs a multilayered statistical model, and further digs out the nested relationship among the factors, so as to analyze the influencing factors of IEE in depth.

The contribution of this paper to the existing research is mainly reflected in the following aspects: (1) the study combining the embeddedness theory with the study of IEE and summarizing the social embeddedness of IEE from different dimensions, respectively, which provides a new vision for exploring the influencing factors; (2) disentangles the moderating relationship between the social embeddedness factors and the essential direct factors, and broadening the method field of empirical analysis of industrial eco-efficiency; (3) reveals the role mechanisms of industrial eco-efficiency influencing factors, which helps us further to analyze the reasons for changes in industrial eco-efficiency and provides a reference for government departments to formulate directional and characteristic strategies. In addition, in the empirical analysis, the big data (Baidu index) was used to characterize the degree of group cognition, reflecting the influence of big data on decision-making.

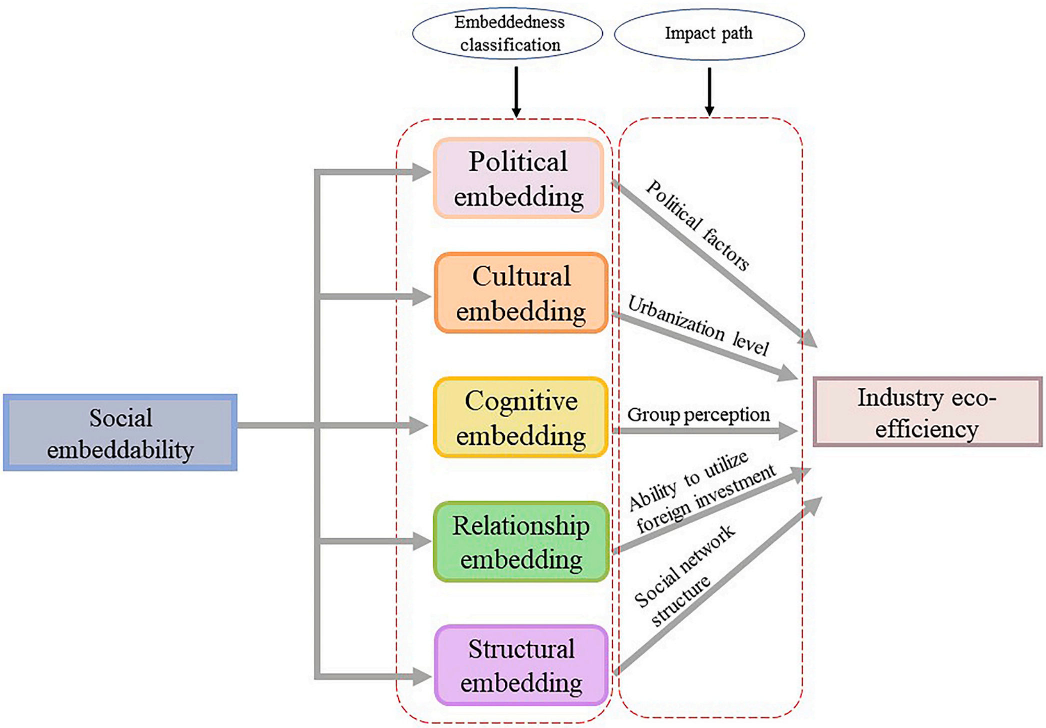

Fig. 1. Theoretical framework.

2. Social embeddedness of industrial eco-efficiency

Social embeddedness theory points out that economic individuals are always moderately embedded in social networks, emphasizing the integration of economic individuals into the social system for in-depth study [29]. Most of the previous studies focused on selecting indicators for eco-efficiency, ignoring the impact of social context elements [30]. For the YRB in the context of high-quality development, focusing on the influence of social embeddedness factors has special meaning for realizing the improvement of IEE. Therefore, it is necessary to introduce the social embeddedness theory when analyzing the path mechanisms of factors affecting IEE.

Although scholars have conducted more studies on embeddedness theory, it is challenging to define embeddedness that can be universally accepted [31] and different classifications of embeddedness have been made. Based on the definitions of political, cultural, cognitive, relational, and structural embeddedness by Gulati [32] and Zukin [33], this paper proposes an "embeddedness" view of the factors affecting IEE and generalizes the social embeddedness of the factors affecting IEE (Fig. 1).

Political embeddedness refers to the influence of the political system and power structure of each municipality on the IEE of each municipality, it reflects the importance of each municipality in industrial development. This includes the degree of financial support from municipalities for industrial economic development. Political embeddedness mainly focuses on the mechanism of the influence of political factors on the growth of IEE. For example, the impact of the scale of science and education expenditure on IEE in municipalities in the YRB. Pan et al. found that fiscal science and education expenditure is an essential determinant of IEE in the east-central region of China. The scale of fiscal science and education expenditure should be further increased [34].

Cultural embeddedness refers to the impact of social and cultural factors, such as the social values and social rules of each municipality on IEE. Owing to the large area of the Yellow River and its wide basin, differences in levels of economic development and urbanization between regions cause differences in social and cultural factors, such as behavior and humanistic quality, among municipalities, which have different constraints and impacts on IEE.

Cognitive embeddedness refers to group thinking and group cognition, which are formed during the process and activities of economic development. Group thinking and cognition significantly influence the behavioral decisions and other economic activities of industrial enterprises in each region. This paper measures cognitive embeddedness through the Baidu index. Although search engines have problems such as slow database updating and biased result credibility, their fast search speed and comprehensive content coverage have deepened the public's reliance on search engines, and along with the development of industrial "Internalization," it is possible to respond to the public's thinking and cognition through online search behavior. The Baidu index is based on Baidu user behavior data, is the dimension of the search volume, and can reflect the public's habits and perceptions economic subjects [35].

Relational embeddedness refers to viewing IEE as a node in a social network relationship, where the network relationship changes IEE. Relational embeddedness focuses on the social network relationships that bring information and resources affecting IEE to industrial industries in each city. Municipalities differ in their ability to access foreign investment, which affects IEE due to location conditions and resource endowment [36].

Structural embeddedness refers to the general structure formed by industries in each municipality during economic development. The structural embeddedness concern emphasizes the overall function and structure of the network formed by each urban industry and the structural position of each urban industry as a network node in the social network and its relationship with the IEE. The excess

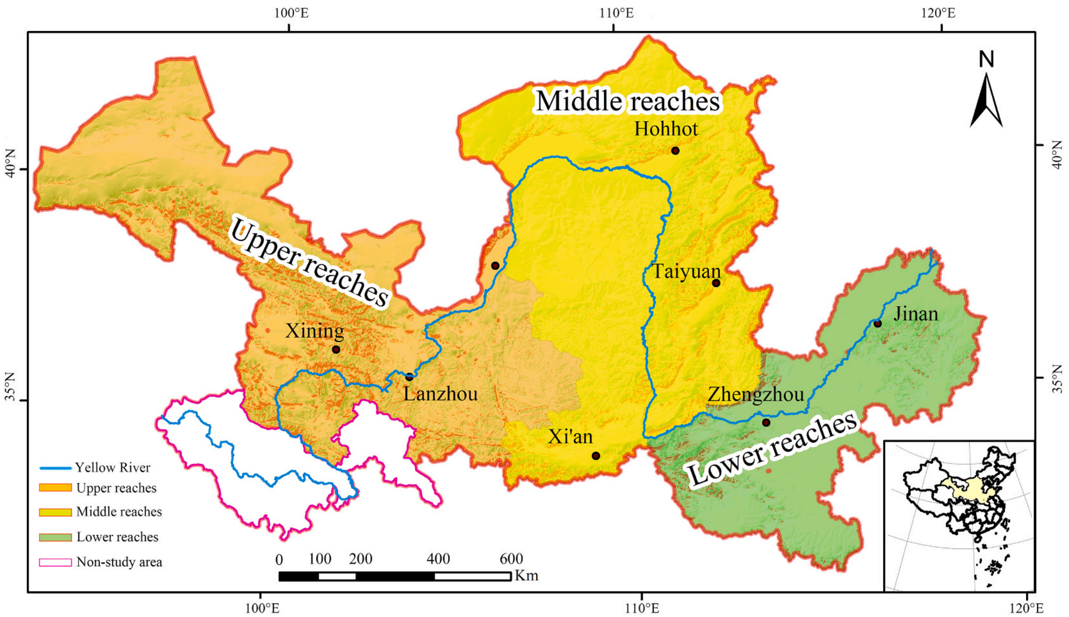

Fig. 2. Research area.

value (including information and resource advantages) generated by this structure significantly impacts IEE. For instance, what will impact IEE from the large proportion of a city's secondary industry output to the total secondary industry output of the YRB?

3. Methods and data

3.1. Study area

In this study, based on ensuring the integrity of the basin scope and considering the integrity of provincial and municipal administrative divisions and the relevance of local and regional development to the YRB, eight provinces and regions through which the Yellow River flows were selected as the study area, excluding Sichuan Province and the four allied cities in Inner Mongolia as well as some areas with serious data deficiencies (Fig. 2). According to the Outline of the Yangtze River Economic Belt Development Plan, Sichuan is not included in the YRB, and the four eastern allied cities are included in the Northeast Revitalization Plan, so the areas mentioned above are not included in the study area. For analysis, the YRB was divided into upper, middle, and lower reaches by based on the results of a previous study [37,38] and by combining topography, geomorphology, and other natural factors. Qinghai, Gansu, and Ningxia provinces were designated as the upper reaches; Inner Mongolia, Shaanxi, and Shanxi provinces as the middle reaches; and Henan and Shandong provinces as the lower reaches [39].

3.2. Super-SBM model

Data Envelopment Analysis (DEA) is a method of evaluating the relative effectiveness of decision-making units with multiple inputs and outputs by using a data envelopment analysis model to obtain the corresponding production frontiers based on known data. The DEA method is more careful consideration of the application of non-expected output indicators in the model, to a large extent, to maintain the original data information, and in the calculation of the principle of the use of statistical methods to give weights to the indicators directly to make up for the defects of the use of subjective assignment of weights, can be the more effective and correct measurement of IEE.

Traditional DEA model do not reflect slack improvement in efficiency measurements when the slack in inputs or outputs is non-zero, and tend to overestimate the efficiency of decision units [40]. To address input and output slack, Tone [41]. proposed a non-radial, non-angular approach to DEA analysis based on the measurement of slack variables, known as the SBM model. The advantage of this method is that its inputs and outputs are a dimensionless dimension, which does not affect the efficiency value. The efficiency value monotonically decreases with the degree of slack in inputs and outputs. However, there will be a situation in which more than one decision-making unit is the same as being fully efficient (with an efficiency value of 1), as well as the impossibility of evaluating and ordering these decision-making units efficiently. Given this, Tone further proposed the Super-SBM model based on the modified relaxation variable [42]. The Super-SBM model allows decision-making units (DMUs) to have an efficiency value of ≥1, which further distinguishes effective DMUs and avoids the problem that effective DMUs cannot be compared. In summary, in order to measure the industrial efficiency of the YRB more accurately, this paper chooses the Super-SBM model that considers global, non-angle, and non-expected outputs. The model can be expressed as follows:

$$\theta^* = \min_{\lambda,s^s,s^+} \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x^t}}{1-\frac{1}{q+h}\left(\sum_{r=1}^{q}\frac{s_r^+}{y_{ro}^t}+\sum_{k=1}^{h}\frac{s_k^-}{b_{ko}^t}\right)} \tag{1}$$

Subject to

$$x_{to}^t \geq \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda^t x_j^t - s_i^- \quad i=1,2,\ldots,m;$$

$$y_{ro}^t \leq \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda^t y_{rj}^t + s_r^+ \quad r=1,2,\ldots,q$$

$$b_{ko}^t \geq \sum_{t=1}^{T}\sum_{j=1,j\neq o}^{n}\lambda^t b_{kj}^t - s_k^- \quad k=1,2,\ldots,h$$

$$\lambda_j^t \geq 0(\forall j), s_i^- \geq 0(\forall i), s_r^+ \geq 0(\forall r), s_k^- \geq 0(\forall k).$$

where i, r, k denote the number of inputs, desired output, and non-desired output variables, respectively, λ represents the weight variable, the input variable is x_{to}^t, the desired output is y_{ro}^t, and non-desired output is b_{ko}^t. s_i^-, s_r^+, and s_k^- are the slack variables, The subscript o indicates the evaluated decision-making unit. θ^* denotes the relative efficiency value, and $\theta^* > 0$. A larger value of θ^* represents a higher level of efficiency.

3.3. Hierarchical linear modelling

Hierarchical linear modelling is one of the most commonly used advanced statistical methods [43] commonly used in the social sciences to analyze data at multiple levels, which can take into account information between groups (at the aggregate level). When performing regression analysis of data, it checks for between-group differences in the dependent variable between groups, determines whether the data have a nested structure [44] allows for the inclusion of both individual- and group-level independent variables in the analysis, and takes into account the effects of both group-level variables and individual-level variables on the individual dependent variable or outcome variable [45]. In addition, the reliability, correlation coefficients, fixed effects, and random effects of the hierarchical linear modeling results are valuable in analyzing the problem under study [46]. Compared with the traditional OLS and spatial measurement models, the HLM model overcomes the limitations of the traditional measurement methods in dealing with nested data [47]and can consider the impact of higher levels of data and analyze the relationship between data at different levels; moreover, the HLM can calculate the covariance at different levels efficiently and more accurately examine the cross-level influence mechanisms of the underlying and embedded variables Therefore, because IEE is characterized by social embeddedness, HLM is more suitable for analyzing IEE influencing factors. The HLM used in this study comprises three models. First, a null model was constructed to understand the intra-group correlation coefficient (ICC) and determine whether the data were suitable for analysis using HLM. A random coefficient regression model was used to analyze the effects of the fundamental variables on IEE and to determine whether the intercept and the coefficients of the fundamental variables differed significantly between different municipalities. A random intercept and random slope model were constructed to analyze further the effects of social embeddedness factors of the IEE.

The null models were used to decompose the variation in IEE in the YRB into components that can be explained by level 1 (fundamental factors) and level 2 (social embeddedness factors). The null model consists mainly of equation (2) and equation (3).

$$\text{Level 1}: IEE_{ij} = \beta_{0j} + r_{ij} \tag{2}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{3}$$

where $i = 2006, \dots 2019$ denotes year i and $j = 1, \dots 61$ denotes the j-th municipality. β_{0j} denotes the random effect between municipalities and γ_{00} denotes the average effect between municipalities. *IEE* epresents industrial eco-efficiency. The ICC-value can be calculated using equation (4) and used as a coefficient to consider reliability.

$$ICC = \frac{{\sigma_2}^2}{{\sigma_2}^2 + {\sigma_1}^2} \tag{4}$$

where σ_1^2 denotes the variance component of the error term in level 1 (within-group variance), and σ_2^2 denotes the variance of the error term in level 2, also known as the between-group variance. A larger ICC—value means that the between-group variance explains more of the total variance, indicating that the data have nested characteristics and require the use of the HLM; if the obtained value tends to zero, it proves that the results obtained using the least squares regression have high confidence.

We construct the random coefficient model (RCM) through equations (5)–(9):

$$\text{Level 1}: IEE_{ij} = \beta_{0j} + \beta_{1j}GPC_{ij} + \beta_{2j}IA_{ij} + \beta_{3j}ER_{ij} + r_{ij} \tag{5}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{6}$$

$$\beta_{1j} = \gamma_{10} + \mu_{1j} \tag{7}$$

$$\beta_{2j} = \gamma_{20} + \mu_{2j} \tag{8}$$

$$\beta_{3j} = \gamma_{30} + \mu_{3j} \tag{9}$$

where β_{1j}, β_{2j} and β_{3j} are the slopes of GPC, IA, and ER, respectively; γ_{00} is the average of the intercepts, and γ_{10}, γ_{20} and γ_{30} are the averages of the corresponding slopes.

Stochastic slope intercept model (SIM):

$$\text{Level 1}: IEE_{ij} = \beta_{0j} + \beta_{1j}GPC_{ij} + \beta_{2j}IA_{ij} + \beta_{3j}ER_{ij} + r_{ij} \tag{10}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \gamma_{01}UR_j + \gamma_{02}STR_j + \mu_{0j} \tag{11}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}NI_j + \gamma_{12}UR_j + \mu_{1j} \tag{12}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}GER_j + \gamma_{22}ECO_j + \mu_{2j} \tag{13}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31}UR_j + \mu_{3j} \tag{14}$$

The explanatory variables in the SIM were group-centered.

3.4. Variables

3.4.1. Base variables description

The following variables were selected based on the theory of factors influencing IEE and social embeddedness:

In the level 1 model, the dependent variable was IEE in the YRB.

The level 1 independent variable: GDP per capita expressed as logarithm of per capita GDP per capita population (GPC), was used to characterize the level of economic development. The economic factors are major determinants, an essential indicator of a region's comprehensive strength, and the level of industrial agglomeration (IA), were calculated using locational entropy [48]. Different levels of industrial agglomeration lead to varying economic growth rates. Although industrial agglomeration can improve eco-efficiency through channels such as scale effects and green technology, excessive industrial agglomeration can cause problems such as environmental pollution [49] and reduce IEE. Environmental regulation (ER), the intensity of urban ER is reflected by the total utilization rate of industrial solid waste. It is difficult to effectively improve environmental quality by only relying on market regulation, and the government needs to regulate and regulate [50]. Under ER, the environmental technology of the industrial sector is improved and industrial pollution emissions are effectively controlled, thus affecting IEE.

The location entropy is calculated by the following equation (15):

$$IA = \left(E_{ij}/E_j\right)/\left(Q_{ij}/Q_j\right) \tag{15}$$

where E_{ij} is the industrial GDP of the city i in year j, E_j is the national industrial GDP in year j, Q_{ij} is the urban GDP of city i in year j, and Q_j is the national GDP in year j.

3.4.2. Industrial eco-efficiency index selection

Building a scientific index system is a prerequisite for practically evaluating IEE. The target layer was divided into two layers based on the availability and scientificity of data: input and output. This study selects industrial value added as the economic value indicator, and industrial wastewater, total industrial solid waste, and industrial sulfur dioxide generation as ecological pressure indicators (Table 1).

3.4.3. Description of social embeddedness indicators

Social embeddedness variables were introduced to more comprehensively analyze the factors influencing IEE. Combining data availability with the definition of embeddedness factors given by Liu and Wang and others [51,52], the political embeddedness was represented by the average share of science and education expenditure in GDP (GER). The cognitive embeddedness was replaced by the Baidu index of the industrial economy (NI), which is represented by the average of the Baidu index in the cities of the YRB. The cultural embeddedness was expressed as the average urbanization rate (UR) of each city; the relational embeddedness was expressed as the average of the proportion of actual foreign capital utilization to GDP (ECO) of each city; and the structural embeddedness is expressed as the average of the ratio of secondary industry output value of each city to the total secondary industrial output value of the YRB (STR).

3.5. Data sources

The indicators involved in IEE measurement were mainly obtained from the 2007–2020 China City Statistical Yearbook (CCSY), provincial statistical yearbooks, statistical yearbooks of each city and water resource, and other statistical bulletins. In the level 1 model, GPC、IA and ER were obtained from the provincial environmental statistics annual reports, and relevant yearbooks of each city. In the level 2 model, the Baidu index of the industrial economy was obtained by integrating the search frequency of "industrial economy" in the Baidu index (PC), The expenditure on science and education, UR, actual utilization of foreign capital, and the proportion of industrial output value were compiled from the Chinese urban Statistical Yearbook (2007–2020). In order to eliminate the interference of the fluctuation of the price level, the price variable is deflated with the year 2006 as the base period. Table 2 describes

Table 1
Industrial eco-efficiency evaluation index system.

Target layer	Guideline layer	Indicator layer	Unit	Mean	Std. Dev	Maximum	Minimum
Inputs	Resources	Industrial water consumption	10,000 tons	18,493.57	15,791.49	206,000.00	120.00
		Industrial electricity consumption	10,000 kWh	1,079,916.54	1,333,620.83	12,171,304.00	4200.00
	Capital	Total assets of industrial enterprises	100 million yuan	2418.40	2171.34	13,556.64	71.43
	Labor	Industrial employees	persons	157,448.11	118,037.20	801,872.00	3900.00
Outputs	Desired Output	Industrial added value	100 million yuan	801.00	739.95	11296.73	22.93
	Non-desired output	Industrial wastewater emissions	10,000 tons	5924.37	5090.63	28,191.83	122.26
		Industrial SO_2 emissions	tons	66,717.56	56,836.32	337,164.33	917.27
		Industrial solid waste	tons	45,590.91	210,245.11	5,168,812.16	296.02

the data sources and measurements.

4. Results and discussion

4.1. Results of industrial eco-efficiency measurement

In this chapter, we bring the indicators in Table 1 to Eq. (1) and measure them to obtain the final IEE. Table 3 lists the statistical characteristics of IEE, which show that IEE is increasing.

4.2. Regional differences in industrial eco-efficiency

2006–2019, the urban industrial economy developed rapidly, intensifying the conflict between economic development and ecological protection. The Chinese government has enacted many relevant laws to establish an "eco-friendly" industrial development model [53]. This is a critical period for transforming economic development in the YRB from "high growth" to "high quality.". Given this, combined with the trend of IEE, 2006, 2010, 2015, and 2019 were selected as the primary time points to plot the change in nuclear density curves (Fig. 3) to gain a comprehensive understanding of the spatial and temporal evolutionary trends within IEE at different points in time.

Overall, the IEE of the YRB shows a fluctuating rise as a whole and an N-shaped rising trend by stages. In three time periods 2006–2010, 2010–2015, and 2015–2019, the center of IEE nucleus density first appears rightward, then shifts leftward and then rightward, indicating the IEE of these cities grows and then decreases, and then continues to grow, with an unstable dynamic of change between concentration zones. Owing to financial shock, IEE declined during the period of 2010–2015 [54]. Although the country has introduced positive fiscal policies, the external environment has not been effectively improved [55], enterprises are not willing to invest, and the investment amount is reduced. Additionally, industrial enterprises have pursued economic speed and neglected development quality, which disrupted the balance between industrial development and environmental management, causing a decline in IEE. The "peak" of the nuclear density curve decreased compared to 2006, and the peak shape changed from a "sharp peak" to a "broad peak," indicating that the IEE varies greatly among cities, and industrial development polarization was also observed. The value of nuclear density in the upstream area is higher than that in the middle and downstream areas, and it is more concentrated in the low-level range. The upstream area is rich in coal mining resources, and the development of some cities is overly dependent on resource development. Compared to the middle and downstream cities, the production methods are brutal, the industrial structure is upgraded slowly, and the investment in environmental protection is insufficient, which leads to low IEE.

The beginning of the left end of the curve gradually shrank toward the middle, and the right tail of the kernel density curve was significantly higher, indicating that the IEE in these regions has improved and developed well over time. In this regard, cooperation and communication among regions should be strengthened, high-efficiency regions aid in maintaining momentum, and low-efficiency regions should further strengthen the upgrading and transformation of enterprises to narrow the regional gap.

From a spatial perspective (Fig. 4), the level of IEE in upstream areas is lower than in middle and downstream areas. An overall low level of IEE in 2006 was observed in the YRB, with the upstream and midstream regions dominated by low and medium efficiency. In contrast, the middle and downstream regions had higher IEE, but the radiation range was smaller. In 2010, urban IEE improved compared to the overall 2006, 19 cities were at medium and above efficiency level. In 2015, the level of IEE in the upper, middle, and downstream regions generally decreased, with 34 cities in the low-level region. Compared to 2010, the difference in IEE between municipalities within the same province decreased. In 2019, the "joint" development of space was prominent, IEE showed a trend of concentrated contiguity. IEE improved substantially compared to previous years; twenty cities entered the high-efficiency tier. The proportion of upstream and midstream cities in the high-efficiency zone increased, and the difference in IEE among cities was evident.

4.3. Analysis of empirical results

The null model was used to calculate the intragroup correlation coefficient (ICC) and to evaluate the applicability of HLM to determine whether a multi-layer statistical model was to be constructed.

As shown in Table 4, the intragroup correlation coefficient was 0.5079 (0.0408/(0.0395 + 0.0408)), indicating that 50.79% of the variation in IEE in the YRB can be explained by social embeddedness factors and 49.21% of the variation can be explained by

Table 2
Data and sources.

Variables	Symbol	Measurement	Sources
Level of Economic Development	GPC	GDP per capita (million yuan/person)	CCSY
Industrial Agglomeration	IA	Location entropy	CCSY
Environmental Regulation	ER	Comprehensive utilization rate of industrial solid waste (%)	CCSY
Political Embeddedness	GER	Scale of science and education expenditure/GDP × 100 (%)	CCSY
Cultural Embeddedness	UR	Level of urbanization (%)	CCSY
Cognitive Embeddedness	NI	Industrial Economy Baidu Search Term Frequency	Baidu Index (PC)
Relational Embeddedness	ECO	Total utilized foreign capital/GDP × 100 (%)	CCSY
Structural Embeddedness	STR	Municipal industrial output/Total industrial output × 100 (%)	CCSY

Table 3
Descriptive statistical data of industrial eco-efficiency.

Year	Mean	Minimum	Median	Maximum	Std. Dev
2006	0.3527	0.0708	0.2142	1.1499	0.3362
2007	0.3821	0.0251	0.2041	1.1881	0.3603
2008	0.2657	0.0474	0.1639	1.1858	0.3025
2009	0.2963	0.048	0.1739	1.2979	0.3144
2010	0.4197	0.0956	0.3362	1.2364	0.3132
2011	0.3466	0.0691	0.169	1.2924	0.3701
2012	0.3683	0.0393	0.1875	1.2895	0.3819
2013	0.4834	0.1613	0.3338	1.2974	0.3382
2014	0.4011	0.1401	0.2861	1.1838	0.3042
2015	0.3559	0.0613	0.1751	1.1163	0.3515
2016	0.588	0.1412	0.4504	1.1963	0.345
2017	0.6291	0.1706	0.5956	1.1644	0.3265
2018	0.5931	0.1236	0.4822	1.2439	0.3675
2019	0.5685	0.1231	0.4044	1.2339	0.3775

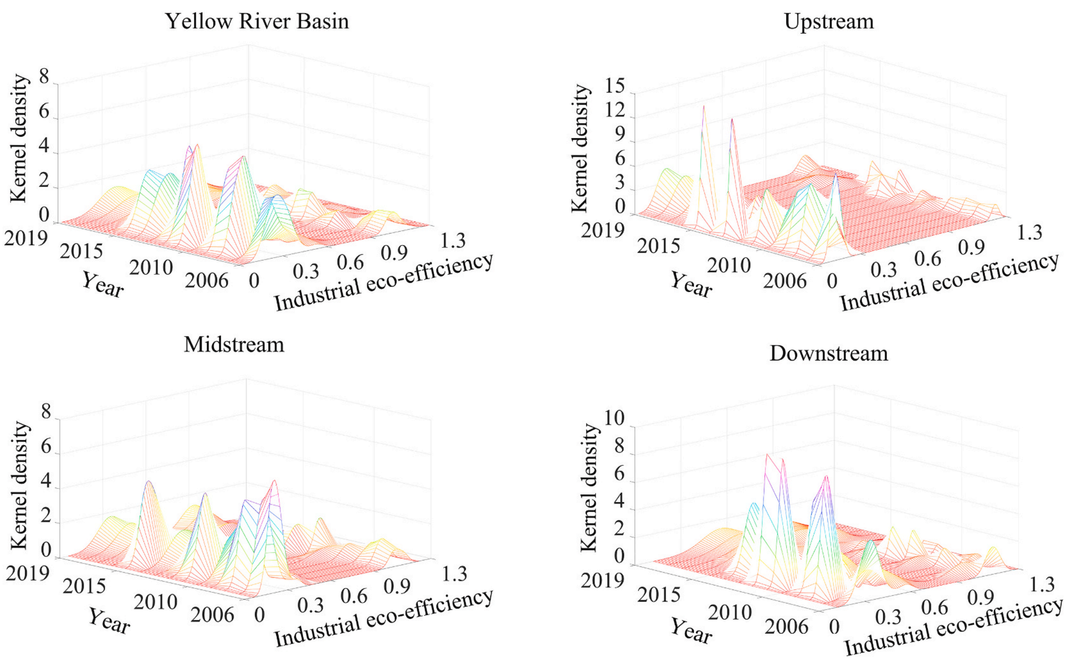

Fig. 3. Kernel density curve of industrial eco-efficiency in major years.

fundamental factors. This also means that the IEE differs significantly among the municipalities. Therefore, when analyzing the factors influencing IEE, it is insufficient only to consider the fundamental variables; social embeddedness variables must be introduced.

4.3.1. Analysis of the results of the RCM

Table 5 shows a significant effect of fundamental factors on IEE. GPC is a significant positive factor with a regression coefficient of 0.3475, which indicates that for every 10,000 yuan increase in GPC, IEE increases by 0.3475 units, implying that an increase in GPC has a positive contribution to the improvement of eco-efficiency. GPC has a direct impact on IEE, and along with the increase of GPC, it stimulates the public's demand for "environmental quality," prompting the relevant departments and enterprises to spend more resources on environmental management and cleaner production [56], which to some extent confirms the relevant content of the environmental Kuznetz curve theory [57]. Meanwhile, in the context of the strategy of high-quality development of the YRB, economic development is more focused on quality and efficiency, which also helps to improve the IEE.

The industrial agglomeration level is a significant positive factor with a regression coefficient value of 0.4732 and is significant at the 5% level, which explains that the improvement of IA level is beneficial to IEE improvement. The increased intensity of IA enables enterprises to generate positive externalities in favor of resource conservation and environmental friendliness through matching, sharing, and learning, which promotes the improvement of IEE. In addition, IA provides favorable conditions for waste recycling among firms, which enhances complementarities among enterprises and reduces pollutant emissions to some extent [58]. This result is consistent with Wu et al. [59].

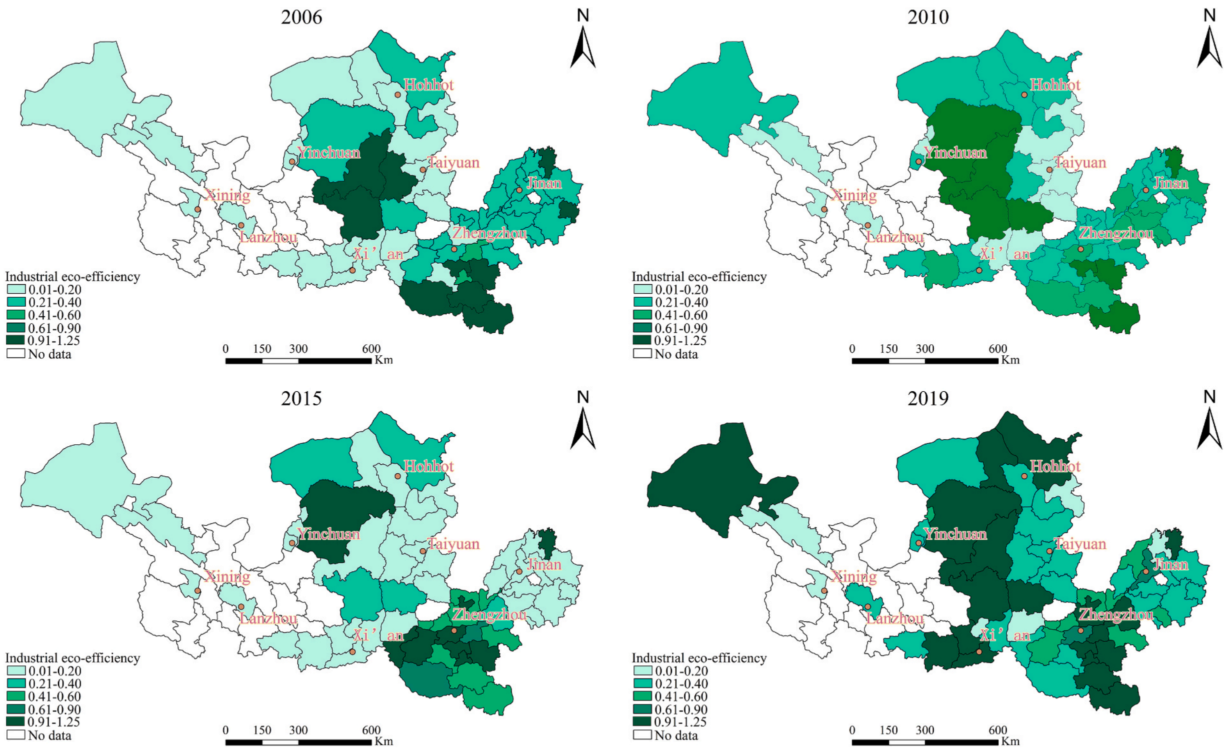

Fig. 4. Spatial distribution pattern of industrial eco-efficiency in major years.

Table 4
Decomposition results of industrial eco-efficiency variation.

Random effects	Standard error	Variance components	Degrees of freedom	χ^2	*p*-value
Level 2	0.2019	0.0408	60	926.9489	<0.001
Level 1	0.1987	0.0395			

Table 5
Results of fundamental factors on efficiency.

Level of explanatory variables	Regression coefficients and significance tests			Variance components and significance test	
	Regression coefficient	Standard error	*t*-ratio	Variance components	χ^2
Intercept 1, β_0	0.320***	0.027	12.068	0.041***	1249.577
Intercept 2, γ_{00}					
GPC slope, β_1	0.347***	0.100	3.471	0.188***	99.944
Intercept 2, γ_{10}					
IA slope, β_2	0.473**	0.185	2.551	0.689***	98.268
Intercept 2, γ_{20}					
ER slope, β_3	−0.147**	0.066	−2.231	0.086***	105.811
Intercept 2, γ_{30}					

Note: ***, ** and * indicate significant at 1%, 5% and 10% significance levels, respectively.

Environmental regulation is a significant negative factor with a regression coefficient of −0.1474 and is significant at the 5% level, indicating that for every 1% increase in ER, IEE decreases by 0.1474 units. Theoretically, the government can control industrial pollutant emissions at the source and improve efficiency by implementing environmental policies [14]. However, ER is negatively related to IEE in the HLM model. The reasons for this are, for one thing, that enterprises do not fully comply with relevant regulations, local government-led ERs lack adequate supervision [60], and the relevant policies are poorly enforced, which leads to the failure of the EIA policy and inhibits IEE. Additionally, the excessive intensity of environmental regulations also leads to a certain extent to costs of environmental governance and inhibits the improvement of IEE.

The results in the variance and significance test section of Table 5 show that the relationship between intercept, GPC, IA, and ER and IEE vary significantly between cities. Introduction of social embeddedness variables is necessary to explain the variations among municipalities.

4.3.2. Results of the social embeddedness impact effect

Based on the regression results of equations (10)–(14), we can analyze the effect of the embeddedness factors. As shown in Table 6, STR is a positive significant factor with a regression coefficient of 5.8528, reflecting the direct influence of structural embeddedness on IEE, with each unit increase in structural embeddedness increasing the mean value of IEE by 5.8528. As the scale of production in the industry continues to expand, the level of industrial agglomeration rises, and the scale effect improves, contributing to the growth of IEE. UR is a significant negative factor with a regression coefficient of −0.5143. This means that cultural embeddedness has a negative effect on IEE. This is different from the results of others. Rapid urban development has brought about ecological problems. Additionally, the YRB is still in the period of transformation of development mode and optimization of economic structure; rapid industrialization is dominant [61], and urban development is overly dependent on resource consumption, which causes a large amount of industrial pollution. At the same time, the "living effect" caused by the rapid development of cities and towns will lead to the expansion of the urban population, which intensifies energy consumption and ecological pollution, leading to the decline of IEE. Previous studies have often assumed that the UR will directly affect IEE [62]. However, we found that UR directly affects IEE and moderates the relationship between other factors and IEE. The results show that an increase in UR will promote a positive relationship between GPC and IEE, reflecting the effect of cultural embeddedness on IEE. For every 1 unit increase in UR, the effect of GPC on IEE will increase by 0.6646 units. The advancement of urbanization provides residents with convenient transportation facilities and employment space, prompting capital agglomeration and raising the per capita economic level. Second, urbanization improves the spatial distribution of cities and rural areas, and the transfer of factors of production from agriculture to industry, pulls economic development and promotes IEE, thus further improving the relationship between GPC and IEE. The slope β_3 equation of the level 2 model variable ER has UR as a negative expectation factor, which indicates that an increase in UR will weaken the negative relationship between ER and IEE, a 1% increase in cultural embedding will reduce the negative impact of ER on IEE by 1.0058 units. The urbanization process reflects the degree of civilization of the city, the higher the urbanization rate, the easier it is for citizens to have good scientific and cultural quality, and the public's demand for the living environment is also improved, which is conducive to the implementation and improvement of environmental regulation, thus promoting the growth of IEE.

In addition, the regression results show that different embedded factors moderate IEE. In the equation of the slope β_1 of the level 2 model variable GPC, NI is the positive expectation factor, and the influence of GPC on IEE increases by 1.3721 units for every 1 unit increase in the Baidu index of "industrial economy" of each city, which indicates that the cognitive embedding will strengthen the positive relationship between GPC and industrial eco-efficiency. Cognitive embedding can be viewed as an embedding of consciousness, and cognition will be reflected in specific behaviors through embedding [63]. By focusing on industrial economic development, the public's ability to regulate their own economic behavior and awareness of industrial economic development is improved, which promotes high-quality economic development and contributes to IEE.

In the equation of slope β_2 of the level 2 model variable, GER is a positive expectant factor, which reflects the influence of political embedment on IEE. The increase in GER strengthens the positive relationship between the variables IA and IEE. When the proportion of GER increases by 1%, the positive impact of IA on IEE increases by 4.1443. The government's strong support for science and education reduces the cost of R&D and increases the level of industrial agglomeration to a certain extent. Furthermore, with the increase of GER, IA is driven to cross the "threshold value," effectively controlling the pollution emission [64] and realizing the improvement of IEE, contributing to the relationship between IA and IEE. ECO is a positive factor, which reflects the impact of relationship embedding on industrial eco-efficiency, indicating that an increase in ECO strengthens the positive relationship between IA and IEE; that is, when the relationship embedding increases by 1%, the impact of IA on IEE increases by 7.499 units. Foreign investment has a technology spillover effect, and this spillover effect promotes industrial agglomeration level [65]. Cities with a high proportion of foreign investment also have relatively large-scale effects of industrial agglomeration, which is conducive to attenuating the negative impact of IA on the environment, thus promoting the positive impact of IA on IEE.

As shown in Table 7, the embeddedness variables can have a good explanation of the degree of variation in the relationship between the intercept, GDP, IA, ER and IEE across the municipalities. This means that the SIM is reasonably constructed.

Table 6
Results of social embeddedness.

Level 1 variable coefficients	Level 2 variable coefficients	Coefficient	Standard error	*t*-ratio	Degrees of freedom	*p*-value
Intercept 1, β_0	γ_{00}	0.320	0.022	13.657	58	<0.001
	γ_{01}	−0.514	0.129	−3.998	58	<0.001
	γ_{02}	5.853	2.250	2.601	58	0.012
GPC slope, β_1	γ_{10}	0.361	0.095	3.807	58	<0.001
	γ_{11}	1.372	0.601	2.282	58	0.026
	γ_{12}	0.664	0.343	1.937	58	0.058
IA slope, β_2	γ_{20}	0.606	0.143	4.237	58	<0.001
	γ_{21}	4.144	1.102	3.758	58	<0.001
	γ_{22}	7.500	1.670	4.490	58	<0.001
ER slope, β_3	γ_{30}	−0.133	0.057	−2.350	59	0.022
	γ_{31}	−1.006	0.483	−2.081	59	0.042

Table 7
Degree of variance component explained by social embedded variables.

Random effect	Original variance	Conditional variance	Degree of explanation
Intercept1, u_0	0.0414	0.0277	33.13%
GDC slope, u_1	0.1882	0.158	16.05%
IA slope, u_2	0.6893	0.1038	84.94%
ER slope, u_3	0.0868	0.0526	39.40%

4.4. Endogeneity test

The above econometric model may have specific endogeneity problems. Its main problem is the reverse causality between the explanatory variables and the explained variables, such as improving the level of economic development will improve the industrial eco-efficiency. However, the improvement of the industrial eco-efficiency will, in turn, promote the improvement of the level of economic development, and lagging the explanatory variables by one period to carry out the test of endogeneity can avoid the endogeneity problem due to the reverse causality to a certain degree. The results show that (Table 8), except for the change in the significance level of a small number of results, the overall regression result is in agreement with the previous one, which means that the main regression result of the previous one is reliable in general.

Based on the social embeddedness perspective, this study summarizes the social embeddedness of industrial eco-efficiency in the YRB, evaluates the spatio-temporal evolution characteristics of industrial eco-efficiency, and explores the influencing factors of IEE to provide a reference for the high-quality development of the YRB. Regarding the spatial and temporal evolution characteristics of IEE, there are apparent differences in IEE among different regions and present a spatial evolution pattern of decreasing from downstream to upstream; regarding the evaluation of the influencing factors, the research results show that the social embeddedness factor can better explain the differences of IEE among cities, but the existing research has not taken the embeddedness of IEE into account. It is necessary to deepen the research to include embeddedness factors in the analytical model and further consider the relationship between embeddedness and IEE to reveal the reasons for the differences in IEE and effectively solve the moderation problem between fundamental factors and IEE. In addition, analyzing the relationship between embeddedness factors and IEE can further explore the role of the informal system and realize the improvement of regional IEE more effectively. This study provides theoretical and empirical evidence for realizing industrial green transformation and ecological protection in the YRB.

5. Conclusions and recommendations

This study measures the industrial ecological effectiveness (IEE) of prefecture-level cities in the YRB from 2006 to 2019 through the Super-SBM model, tries to combine the social embeddedness theory and the multilayer statistical model, constructs the HLM model, reveal the mechanism of social embeddedness on IEE, and further optimize the evaluation system of IEE, expanding the research scope of influencing factors. It is significant for promoting high-quality development in the YRB. The results of this study were as follows.

(1) The IEE of the YRB shows a spatial evolution pattern that decreases from downstream to upstream, with an overall increasing trend accompanied by interannual fluctuations, and significant spatial and temporal differences in IEE among municipalities. IEE is higher in the eastern region, improves faster in the central region, and has more room to increase in the western region.
(2) The embeddedness variable can explain 50.81% of the variance, so when formulating policies for high-quality development of industries in the YRB, it is essential to consider both primary and social embeddedness factors.
(3) The HLM results show that GPC, IA, and structural embeddedness were significant positive direct influencing factors, and ER and cultural embeddedness were significant negative direct influencing factors. Social embeddedness can also regulate the relationship between direct influence factors and IEE. Specifically, cognitive and cultural embeddedness positively regulate GPC and industrial eco-efficiency; political and relational embeddedness positively regulate IA and industrial eco-efficiency; and cultural embeddedness weakens the negative relationship between ER and industrial eco-efficiency.

Table 8
Endogeneity test results.

Level 1 variable coefficients	Level 2 variable coefficients	Coefficient	Standard error	t-ratio	Degrees of freedom	p-value
Intercept 1, β_0	γ_{00}	0.3247	0.0236	13.748	58	<0.001
	γ_{01}	−0.5253	0.1286	−4.085	58	<0.001
	γ_{02}	6.3155	2.2356	2.825	58	0.006
GPC slope, β_1	γ_{10}	0.3873	0.0965	4.014	58	<0.001
	γ_{11}	1.8178	0.7703	2.36	58	0.022
	γ_{12}	0.2833	0.3191	0.888	58	0.378
IA slope, β_2	γ_{20}	0.679	0.1953	3.476	58	<0.001
	γ_{21}	3.977	1.8186	2.187	58	0.033
	γ_{22}	8.9937	2.4301	3.701	58	<0.001
ER slope, β_3	γ_{30}	−0.0725	0.043	−1.687	59	0.097
	γ_{31}	−0.5049	0.3772	−1.338	59	0.0186

The following recommendations are proposed considering the above findings.

(1) Deepening the potential of essential factors to enhance IEE. The results show that the level of economic development and industrial agglomeration has a significant positive effect on IEE. Municipalities should further improve the level and quality of economic development and promote the integration of economic development and environmental protection industries; give full play to the positive externality of industrial agglomeration; upgrade the level of craftsmanship and promote IEE. ER inhibits IEE, indicating that there are still many problems with the existing environmental policy regarding system design and policy implementation. It is necessary to accelerate the policy innovation of the environmental system and strengthen the market concept of environmental legislation.
(2) Optimize the impact of social embeddedness factors on IEE. Optimize the positive moderating effect of cognitive embedded factors on industrial eco-efficiency. Enterprises should further improve the “Internet + Industry" development model and enhance industrial digitization and networking. Strengthen the popularization of industrial knowledge on the Internet and provide a convenient platform for the public to understand industrial development. Optimize foreign trade relations. Relationship embeddedness promotes industrial eco-efficiency, and investment facilitation should be strengthened to broaden foreign investment channels and optimize the investment environment. Optimize the industrial structure and pollution management model. On the one hand, the government should increase support for high-tech industries, eliminate high energy-consuming industries, and actively layout emerging industries; on the other hand, optimize the urban layout, improve resource utilization, and avoid excessive emissions and overcapacity. Optimize the financial expenditure structure of the YRB and take advantage of the coordination of political embedding. Based on strengthening control over the outflow of scientific research funds, R&D investment should be increased. At the same time, enterprises should be encouraged to carry out scientific research cooperation to promote the development of the industrial level to a high level, thus improving IEE.
(3) Build consensus, deepen cooperation, and categorize policies. The study results show apparent differences in IEE in the upper, middle and lower reaches of the YRB, and it is necessary to subdivide the industrial sector according to the characteristics of the regional industrial base and resource endowment. When formulating policies, it is necessary to enhance the overall situation, establish a coordinated development mechanism, strengthen intra-regional linkage, further improve the factor flow mechanism, and plan the industrial layout in an integrated manner, but also to avoid the “siphon effect", fully tap the favorable factors, prevent the excessive loss of resources and factors in small and medium-sized cities, and promote openness and innovation, to turn disadvantageous into advantageous.

Although we have made some discoveries about the role paths of factors affecting IEE under the embeddedness perspective, this study still has some limitations. First, there are fewer sample cities in the central and western parts of the country due to the limitation of data acquisition; second, the research on the characteristics of regional heterogeneity in the upper, middle and lower reaches of the YRB needs to be deepened. In the future, the differences in the impact of influencing factors in different regions on IEE can be explored from the scales of urban agglomerations, prefectural and municipal distributions, and city types by combining them with the theory of regional heterogeneity.

Funding

This study was supported by Henan Province Philosophy and Social Science Planning Project (Program No. 2022CJJ135), Henan Province Higher Education Teaching Reform Research and Practice Project (Program No. 2021SJGLX430), Henan Province Soft Science Research Program Project (Program No. 232400410371; 232400411162).

Data availability statement

Data available on request from the authors.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Junjie Wang: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Zhun Chen:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Taizheng Chen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis. **Wei Wang:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Bailu Liu:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation.

Declaration of competing interest

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

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