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Preventing COVID-19 from the perspective of industrial information integration: Evaluation and continuous improvement of information networks for sustainable epidemic prevention

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ABSTRACT

COVID-19 is accelerating industrial information integration (III) for sustainable epidemic prevention and innovation design. It is important to emphasize that this interaction makes it reciprocal. To prevent COVID-19, the III of industrial sectors should be strengthened to encourage innovation for sustainable epidemic prevention. Accordingly, we studied the overall dynamic change trend of industrial sectors' information integration networks (IIN), the characteristics of individual IIN, and their influence on IIN performance. In the study, the gravity model and social network analysis were used to determine the variables of industrial sectors' information distance and quality, and to construct the IIN of industrial sectors. The results show that the overall relevance of the IIN of industrial sectors is low, and the network density fluctuates, with high network efficiency and poor stability. Two-way, strong correlation between industrial sectors is relatively low. The spillover effect of industrial sectors in the upstream of the industrial chain is poor, and it is difficult to have a strong information integration driving effect on the downstream industrial sectors. The interplate linkage of the IIN of industrial sectors is insufficient. Compared with point centrality and closeness, improvement of the betweenness centrality of industrial sectors can significantly improve IIN performance.

1. Introduction

The unexpected novel coronavirus of late 2019 has shattered many people's plans. **China has actively respond to control COVID-19.** At present, the disease has been effectively controlled in China. However, as of June 1, 2020, the global spread of coronavirus is still very serious, and the whole human race faces a serious test. There is no doubt that COVID-19 causes damage to material production and a threat to human life and health [1]. COVID-19 is an emergent public health event, and its infectivity and danger will have a great impact on the development of industrial information networks in the long term. On the one hand, COVID-19 is accelerating industrial sectors' information integration for sustainable innovation design and epidemic prevention [2]. On the other hand, industrial sectors' information integration provides an efficient operational platform for COVID-19 prevention and control [3]. In terms of information networks in epidemic prevention, an information network based on scientific development and technology innovation could be a useful weapon in the fight against diseases [4]. China has made full use of its achievements in terms of scientific and technology innovation in recent years to coordinate the country's research efforts [5]. At the same time, China has provided strong scientific and technological support for the prevention and control of the epidemic through clinical information network cooperation. For example, government departments accelerated the development and application of a science and technology network, and launched 83 emergency response projects. In terms of industrial sectors' information integration engineering, new technologies such as big data and artificial intelligence were made full use of to study and judge epidemic trends and conduct epidemiological investigations [6]. Databases built during outbreaks are used to predict the risk of outbreaks in different regions. 5 G video real-time communication platforms and Internet of Things technologies are used to solve the problem of real-time interaction between epidemiological investigation teams and high-level experts thousands of kilometers away. Information integration tools such as health codes, a communication big data travel card, and epidemic maps have been easy ways for the public to prevent infection [7].

There is no doubt that industrial information integration (III) has played an important role in the response to COVID-19. III is the

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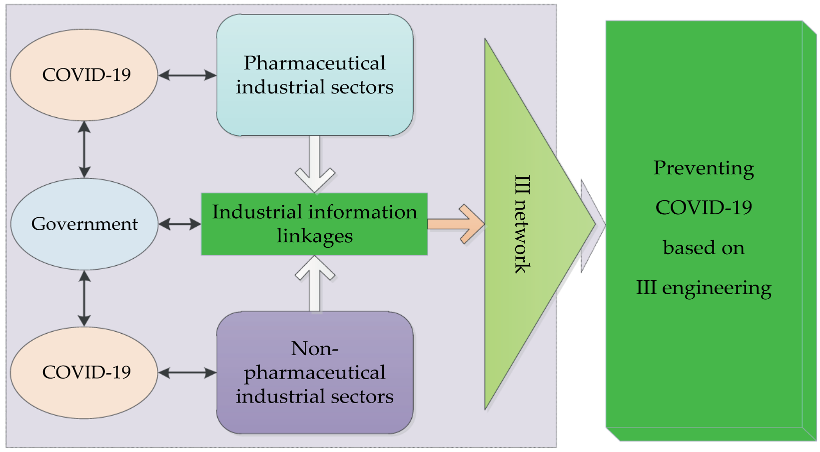

Fig. 1. A framework of the prevention and control of infectious diseases based on III.

foundation of the new era of information and communication technology [8]. In 2005, Xu first put forward the concept of III engineering [9], and information integration has been widely used in various fields of industrial sectors. III is a new concept proposed by the integrated application of emerging information technologies such as 5 G, Internet of Things, big data, cloud computing, wireless communication network, and artificial intelligence in the field of modern industry [10]. The new concept is a very important subject in the industrialization and informatization process, which focuses on the digital and information transformation of industrial sectors [11]. Supply chain management can be used to demonstrate the advantages of III during an emergency response [12]. Supply chains based on III have played a huge role in delivering epidemic prevention supplies in response to COVID-19. The representative industrial Internet of Things is the typical product of III. The Industrial Internet of Things can help enterprises to aggregate and analyze data from sensors to maximize machine efficiency for integrated manufacturing systems and intelligently connected healthcare systems [12]. The medical Internet of things, based on Industry 4.0, has played a key role in healthcare systems [13]. For example, the medical Internet of Things technology has been gradually applied to health identification, diagnosis and treatment, hospital informatization, health management, and other population and health fields. The application is based on communication, electronics, biology, medicine, and other information technologies.

In addition, the epidemic or medical areas application based on III has gradually attracted the attention of some scholars. For example, Agarwal and Searls developed a lightweight method for the drug industry [14]. Subsequently, Wong et al. used multiresolution analysis to study combining process and spectral data [15]. Schaewe et al. studied the application of an image dynamic process to brain monitoring [16]. Xu et al. developed a data access approach in an Internet of Things-based information system for medical services [17]. Horner and Cullen established a database for industrial sector workers with Medicare data [18]. **Chen reviewed the literature on III from 37 research categories, and determined** that information and communication technology is an important factor that causes III to be useful to the medical service field [19]. Da Silva et al. developed a program to integrate technology with medical devices [20]. Ibrahim and Singhal proposed a platform system for reliably retrieving medical information from remote suppliers on demand [21]. Farhad et al. and Deckmyn et al. developed a matched antenna and substrate-integrated compact antenna array, respectively, for industrial, scientific, and medical use [22,23]. Goursaud and Gorce concluded that III is a key technology to support digital cities, healthcare, and the monitoring of the elderly [24]. Xu et al. proposed a circularly polarized antenna for biomedical applications [25]. Namee et al. developed an emergency platform to monitor defibrillator cabinets in medical services [26]. Saadi et al. proposed integrating data mining technology into medical decision support [27]. Wei et al. conducted a survey on geographic visual display techniques in epidemiology [28]. Chen continued to conduct a survey on III in 2016–2019, and noted that research on the pharmaceutical industrial sector mainly concentrated on the practical application of III [29]. Based on the above analysis, III is gradually being used to meet people's medical service needs, such as genomic data, surface electromyography, and so on [30,31]. However, research on the project management of the pharmaceutical industry based on III is rare. The development of the pharmaceutical industry chain is not only based on R&D, production, and marketing, but also is closely related to other industrial sectors [13]. For example, big data analysis and cognitive systems are used to obtain data from wearable devices, which will improve the R&D efficiency of the pharmaceutical sector. Pharmaceutical enterprises can take advantage of the advancement of the Internet of Things to access real-time information during drug sales to improve the visibility of monitoring.

COVID-19 is accelerating III for sustainable epidemic prevention and innovation design. At the same time, COVID-19 epidemic prevention and control has exposed deficiencies in the industrial sectors' information integration networks (IIN) and public health emergency management systems. Major public security incidents involving human safety require large capacity and high-channel information and communication technologies to provide safe and efficient medical services [32]. It has been difficult to establish a cooperative sharing mechanism in data sharing, so it is difficult to share and integrate clinical, basic, and public health data. Project management in the pharmaceutical industry is based on III, which is an important way to prevent and control infectious diseases. Together with other industrial sectors, it forms a set of technologies and concepts based on medical services [33]. The global spread of COVID-19 has led to high requirements for III in various countries. Intelligent medical care based on the deep integration of robotics, big data, and the medical industry involves not only the basic medical industry, but also network suppliers, system integrators, radio equipment suppliers, telecom operators, advanced instrument manufacturing, and other related industrial sectors [34]. Based on the above analysis, the framework of III, applied to the prevention and control of infectious diseases such as COVID-19, is shown in Fig. 1.

The development of III is characterized by scientific and technological innovation and cross-integration. The advancement of industrial technology and medical technology, and the R&D and application of intelligent medical treatment and artificial intelligence, are closely related to the technological innovation and cross-integration of III [35]. The innovation development driven by ecological sharing is the key driving force for the leap-forward development and cross-border integration of III. Collaborative innovation based on III can not only provide a strong guarantee for epidemic prevention, but also can provide preventive measures against other emergencies [36]. Innovation based on III is a development mode and industrial organization form to prevent and control pandemics [37]. The innovation can not only produce a chain reaction in related industrial sections, but also can provide an effective information supply for other sectors and produce a spiral III effect [38]. At the same time, intersector information integration provides the foundation for the innovation, and intersector IIN provides the innovation path [39]. As far as research on industrial sectors' information networks is concerned, many scholars have analyzed it from many aspects. Jin et al. pointed out that technology-intensive manufacturing and materials have become active sectors for innovation information interaction [40]. Feng believes that network density can enhance technological, economic, and social self-reinforcing mechanisms [41]. Fang et al. [42] constructed an industrial sectors information network to analyze its structural characteristics. Hang [43] revealed the network structure characteristics of technology information spillovers. Li et al. [44] used network topology analysis to empirically test the mechanism of sector networks. However, these studies have the following shortcomings. With the incidence matrix constructed by a vector autoregressive model, it is difficult to present the development and preciseness of the industrial sectors' IIN [45]. Moreover, it is impossible to accurately build the industrial sectors' IIN through the keyword search method.

Therefore, we believe that, to make up for the lack of existing research, it is important to study the characteristics of industrial sectors' IIN and analyze the influence of characteristic factors on IIN performance, rather than to study the influence mechanism unilaterally. To make up for the deficiency, this study not only constructs a correlation matrix based on the sector information distance variable and the gravity model, but also studies the industrial sectors' IIN characteristics. In addition, the panel regression model is used to analyze the influence of IIN characteristics on IIN performance. Hence, the research on industrial sectors' IIN has important significance to improve the efficiency and quality of III innovation for COVID-19 prevention and control.

The purpose of this study is to manage the level and mechanism of IIN of the industrial sectors based on innovation linkage to promote III and respond to COVID-19. The contributions of this study are as follows. It reveals the level and mechanism of China's III. In addition, it provides theoretical and practical support for improving the governance level of public health practices from the perspective of industrial linkage.

The study includes the following sections. The study methods and data are presented in Section 2. Section 3 implements the empirical study from four aspects. Section 4 discusses the results of the study. In Section 5, the conclusions and limitations of the study are presented.

2. Study design

2.1. Determination of IIN association

The gravity model is a spatial interaction capability model used to analyze and predict the spatial interaction capability. Many problems, such as the spatial flow of innovation elements [46,47,48], industrial agglomeration [49], and knowledge diffusion [50], have been studied extensively by modifying the coefficients and parameters of the gravity model. For intersector innovation information flow, different strategies exist in the same supply chain, with the product as the link. The heterogeneity of knowledge lends the IIN great attraction [51,52]. The existence of sector information distance enhances the information barrier and impedes the information flow among the network subjects [53]. The gravity model not only considers the information relationship through an input–output table, but also enriches the information quality of industrial sectors. The model accurately constructs the industrial sectors' IIN and describes the dynamic evolution process of the network. Referring to the setting and analogy of quality and distance used by Liu [45] and Yu et al. [54], the study takes innovation information output as the quality variable affecting the information integration attraction. The III correlation matrix can be established as follows:

$$Y_{ij} = K_{ij}\frac{\sqrt[3]{P_i \times E_i \times G_i}\,\sqrt[3]{P_j \times E_j \times G_j}}{D^r{}_{ij}},\ K_{ij} = \frac{E_i}{E_i + E_j}, \tag{1}$$

where Y_{ij} is the attraction relationship; E and P are the innovation information output and input; K is the contribution rate; and D_{ij} describes the sector information distance [55,56].

The input–output table is used to calculate the sector information distance. The input–output table can be expressed as follows:

$$X_i = F_i + Z_i. \tag{2}$$

The above equation can be expressed as follows:

$$X_i = \underbrace{F_i}_{\text{Direct consumption}} + \underbrace{\sum_{j=1}^{N} a_{ij}F_j + \sum_{j=1}^{N}\sum_{k=1}^{N} a_{ik}a_{kj}F_j + \sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} a_{il}a_{lk}a_{kj}F_j + \ldots}_{\text{Indirect consuming}}. \tag{3}$$

The weighted average position measurement method of each sector is as follows:

$$V_i = \frac{F + 2AF + 3A^2F + 4A^3F + \ldots}{X_i} = \frac{(I - A)^{-2}F}{X_i}, \tag{4}$$

where I represents the identity matrix and F is a matrix. If $V_i \geq 1$, then $U_i \in [0, 1]$.

The sector information distance $D_{ij} \in [0, 1]$ is the downstream position [57], and can be expressed as follows:

$$D_{ij} = |U_i - U_j|. \tag{5}$$

2.2. IIN characteristics

(1) At the overall level, we pay attention to the network characteristics of the III network. In this study, network density, network grade, and network efficiency are the key factors. The higher the density, the more connected the IINs are. Network hierarchy refers to the extent to which industrial sectors can be reached asymmetrically. The position of each sector in the network varies greatly, and more industrial sectors are in subordinate and marginal positions. The lower the network efficiency, the more paths there are to reach each other. In the overall network, the higher the resistance to industrial sectors' changes, the smoother the flow of information integration between industrial sectors. The network density can be expressed as follows:

$$\rho = \frac{n}{N(N-1)}. \tag{6}$$

Network correlation is the vulnerability of the IIN, and it can be expressed as follows:

$$R = 1 - \left[\frac{m}{N(N-1)/2}\right]. \tag{7}$$

The network grade can be expressed as follows:

$$GH = 1 - \frac{S}{\max(S)}, \tag{8}$$

where S is the logarithm of points.

The network efficiency can be expressed as follows:

$$GE = 1 - \frac{E}{\max(E)}, \tag{9}$$

where E is the number of redundant lines.

(2) The individual characteristics of nodes are more microscopic, and the network locations of different industrial sectors are investigated

at the individual level. The study mainly investigates the individual level of industrial sectors' IIN in terms of point centrality, betweenness centrality, and closeness. The centrality of a point is closely related to the center of the network. Absolute centrality calculates the absolute value of the number of connections to a node. Relative centrality is the ratio of absolute centrality to the maximum possible degree. Mediation centrality is the position of a network mediation bridge. The more other nodes can be reached through this node, the stronger the control ability of this node. Closeness is concerned with the shortest distance between the point pairs. The closer to the center they are, the shorter the distance is between nodes and other nodes. This is more efficient in the process of information transmission [58]. The added mediation center can be expressed as follows:

$$C_{RBi} = \frac{2\sum_{j}^{n}\sum_{k}^{n} b_{jk}(i)}{n^2 - 3n + 2} j \neq k \neq i, j < k, \tag{10}$$

where $b_{jk}(i) = g_{jk}(i)/g_{jk}$, and $g_{jk}(i)$ is the shortcut number.

Closeness is the average length of the shortest path from each node to the other nodes, and can be expressed as follows:

$$C_{RPi} = \frac{N - 1}{\sum_{j=1}^{n} d_{ij}}. \tag{11}$$

(3) The individual network characteristics in the industrial sectors' IIN are expressed in different plates, and the connection between plates and the role of different plates in the network are analyzed. The study divides plates into four categories according to the number of sending and receiving relations of each plate [59]. The first type is the main beneficiary plate, which mainly shows that the number of relations to receive other plates is greater than the number of relations to send to other plates. The second type is the main spillover plate, which is characterized by more relations sent to the outside than the other plates, and is more active inside. The third type is a bidirectional spillover plate, which is mainly manifested by sending out relations to the plate, and is more balanced compared with the inside of the plate. The fourth type is the broker plate, which has the same number of receiving relations as sending relations. The division of the four types of plates is relative.

Based on the above three dimensions, the structure of the study is as in Fig. 2.

2.3. Data source

The data in the study are from industrial sectors. To make the calculated sector information distance consistent with the national economy industry classification 2017, we selected five industrial sectors from mining, 30 industrial sectors from manufacturing, and three industrial sectors from the power, heat, gas, and water production and supply industrial sectors, totaling 38 industrial sectors. The network quality data were taken from the yearbooks produced from 2013 to 2018. The sector information distance data were calculated according to the basic flow table of the 2017 national input–output table in 2019.

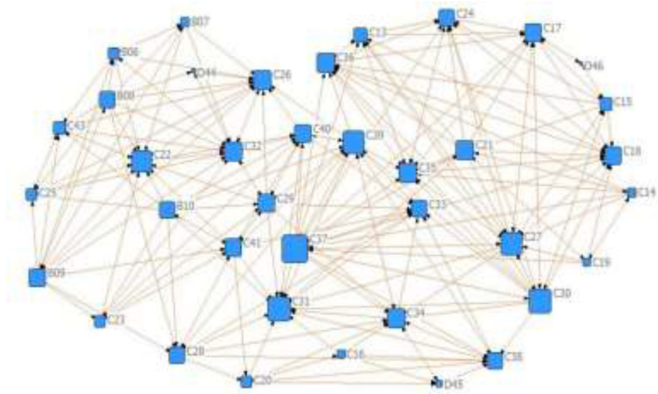

Fig. 3. The industrial sectors' IIN relationship in 2018.

3. Empirical study

3.1. Overall network characteristics

The study constructed the industrial sectors' IIN. The mapped industrial sectors' information integration directed network re shown in Fig. 3. To more clearly and intuitively represent the information integration between various industrial sectors, the node size represents the point centrality. Fig. 4 depicts the dynamic change of the overall network correlation density of the sample during the investigation period. Fig. 5 describes the variation trend of overall network efficiency and network hierarchy.

3.2. Individual network characteristics

The index is used to explore the information integration among various industrial sectors from a micro perspective, and can effectively demonstrate the impact of various industrial sectors on the overall

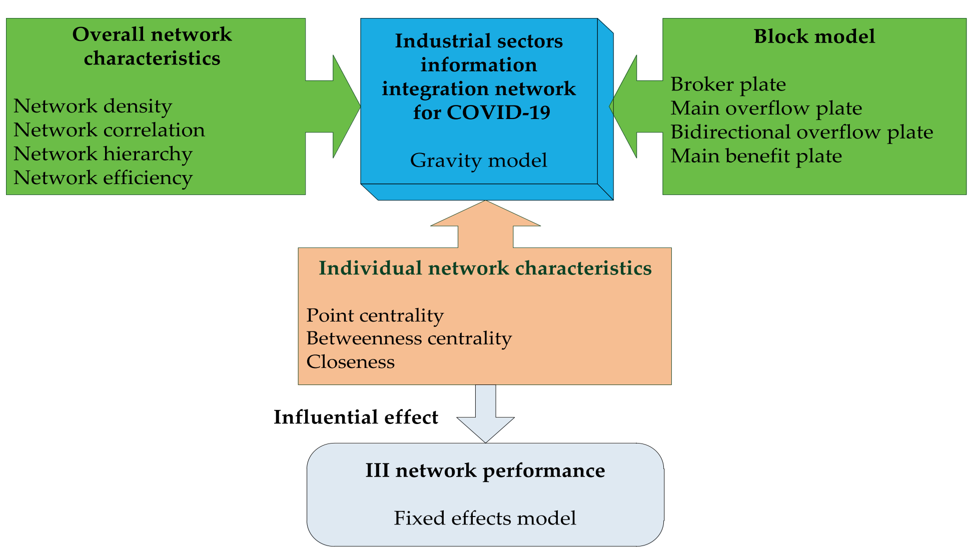

Fig. 2. Research structure.

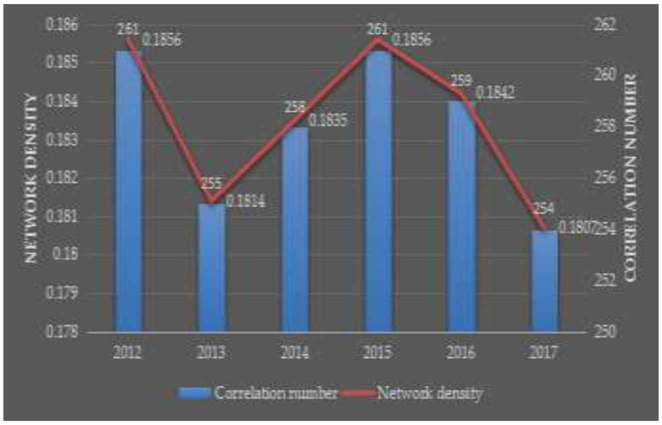

Fig. 4. The network correlation and density.

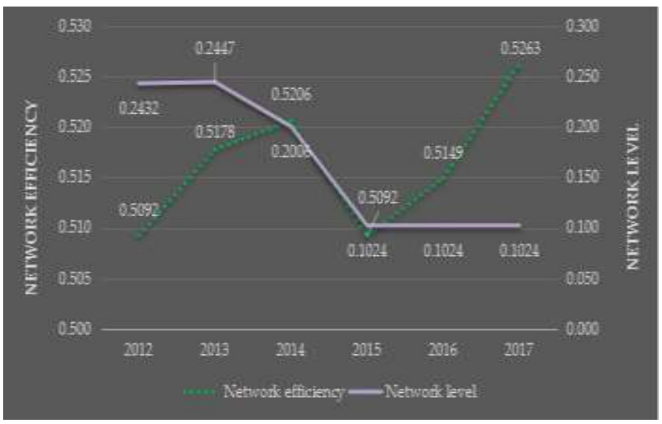

Fig. 5. The network efficiency and level.

industrial sectors' IIN. Based on the three dimensions, we made an in-depth study of the position and role of various industrial sectors. The measurement results of 2018 are shown in Table 1.

3.3. Block model

To systematically analyze the characteristics of 38 industrial sectors' IIN in China, the iterative integration method was used for cluster analysis, and it was divided into four plates. The information overflow between plates is shown in Table 2 and Fig. 6.

3.4. The effect of the network characteristics on network performance

The study focused on how these characteristics can affect the IIN performance of industrial sectors. The performance of individual network characteristics determines the performance of overall network characteristics. We focused more directly on the effect of individual characteristics on IIN performance. The inherent information barriers in some industrial sectors may block information integration in other industrial sectors. Blind pursuit of information integration is likely to lead to the waste of resources and the rise of the marginal cost of innovation. Hence, it is more meaningful to reveal the effect mechanism of the individual characteristics on the current IIN performance, as shown in Table 3.

4. Results and discussion

4.1. Analysis of the overall network characteristics

As can be seen from Fig. 3, there are no isolated points in the 38 industrial sectors as a whole, which indicates obvious IIN characteristics. However, the information correlation between different industrial sectors is relatively heterogeneous. The correlation number gap between industrial sectors is obvious. In Fig. 4, the overall industrial sectors' IIN is a weak correlation and shows a fluctuating trend. The industrial sectors' IIN involves 38 industrial sectors and the maximum number of possible associations is 1406. However, the maximum number of associations in 2012 and 2015 was only 261. From the overall trend, the density of the industrial sectors' IIN shows a trend of first increasing and then decreasing. In 2018, it reached its lowest level, at only 0.1807, with the IIN network showing a loose correlation. As can be seen from Fig. 5, the network hierarchy showed a downward trend and remained stable for the past three years. This shows that the rigid hierarchy of industrial sectors has gradually broken down. Each industrial sector attaches more and more importance to integrated information, and the information linkage effect between industrial sectors is becoming stronger and stronger. More subordinate and marginal industrial sectors are gradually integrated into the information network. Except for 2015, network efficiency has generally presented an upward trend, with a maximum of 0.5263 in 2018. The redundant lines of information correlation between industrial sectors in China are gradually reduced and the stability of the structure is reduced somewhat. The ability of the IIN to resist risks has decreased; it is vulnerable to the collapse of the network caused by the instability of intersector information correlations.

It is found from the dynamic changing trend of the whole network that the overall relevance of the industrial sectors' IIN is not high. To adapt to the new normal of economic development, China made profound adjustments to its industrial policy in 2015 and 2016, which were transition years for the 12th and 13th five-year plans. For the key areas of development, the industrial sectors' development focused on the information and communications technology sector, the high-end equipment manufacturing sector, and the green sector. Cutting overcapacity was the first of five structural reform tasks for 2016. Government departments were determined to close down backward production capacity and actively adjust the industrial sectors' structure, which is in the process of optimization and upgrading. Most industrial sectors that manufacture primary products are gradually changing to manufacture intermediate products and final products. A series of measures led to a turning point in industrial sectors' IIN in 2015 and 2016.

During COVID-19, the domestic economy grew rapidly. Online entertainment, remote work, online education, online medical, fresh e-commerce, and other models have ushered in instant and explosive growth. Like a catalyst, the epidemic has accelerated the transmission speed of communication information, forcing people's living and working habits to move faster. In the future, digital technology will permeate all walks of life, giving birth to the digital economy, a new economic form. The commercial use of 5 G, in particular, will accelerate the digital development of traditional industrial sectors such as energy, medical care, and education. The COVID-19 outbreak could lead to a more diversified and resilient global industrial or supply chain. Although a complete industrial system and complete infrastructure have laid the foundation for the development of China's global industrial chain, it is still difficult to restore the chain in the whole industrial sector. One of the most important reasons is that the efficiency and quality of sharing information in response to pandemics such as COVID-19 is not sufficient for the industrial sectors' response. The role of leading enterprises should be brought into full play to promote industrial chain collaboration based on information and communications technology. In the context of industrial coordination, the industrial sectors should not only enhance the emergency response and coordination ability in the industrial chain and supply chain, but also establish a digital supply chain warning system to identify risks as soon as possible and make preparations. In addition, we should strengthen information and communications technology innovation to improve the

Table 1
Individual centrality analysis of industrial sectors' IIN in 2018.

Sectors	Point centrality						Betweenness centrality		Closeness	
	In	Out	Number of related sectors	Strong integration ratio	Centrality	Rank	Centrality	Rank	Centrality	Rank
B06	4	6	7	42.857	18.919	31	0.025	32	36.634	35
B07	3	5	6	33.333	16.216	33	0.000	35	36.275	36
B08	1	10	10	10.000	27.027	24	2.128	20	41.573	25
B09	3	11	11	27.273	29.730	17	2.159	19	42.045	23
B10	1	10	10	10.000	27.027	20	5.205	9	49.333	13
C13	8	6	9	55.556	24.324	25	0.000	34	41.111	27
C14	2	6	6	33.333	16.216	32	0.060	31	39.362	29
C15	4	8	8	50.000	21.622	26	1.614	22	38.947	30
C16	4	5	5	80.000	13.514	34	0.093	29	39.362	28
C17	8	8	11	45.455	29.730	16	3.732	12	42.045	22
C18	11	5	11	45.455	29.730	18	0.426	25	42.045	24
C19	2	5	5	40.000	13.514	35	0.025	33	38.947	31
C20	6	5	7	57.143	18.919	28	1.178	24	43.529	20
C21	3	12	12	25.000	32.432	12	1.702	21	48.052	17
C22	13	5	13	38.462	35.135	6	3.056	16	46.835	18
C23	5	5	7	42.857	18.919	29	0.221	27	43.529	21
C24	10	4	10	40.000	27.027	24	0.091	30	41.573	26
C25	6	4	7	42.857	18.919	30	0.141	28	38.144	33
C26	12	3	12	25.000	32.432	7	10.114	5	48.684	16
C27	11	11	14	57.143	37.838	5	4.109	11	50.000	12
C28	5	7	10	20.000	27.027	19	6.815	7	50.685	9
C29	6	10	11	45.455	29.730	14	4.12	10	51.389	8
C30	5	13	15	20.000	40.541	3	7.202	6	53.623	6
C31	15	1	15	6.667	40.541	2	12.03	3	58.730	2
C32	12	8	12	66.667	32.432	9	3.163	14	45.679	19
C33	10	1	10	10.000	27.027	22	1.566	23	52.857	7
C34	10	7	12	41.667	32.432	8	6.454	8	54.412	5
C35	12	5	12	41.667	32.432	10	2.647	17	49.333	14
C36	12	6	12	50.000	32.432	11	2.647	18	49.333	15
C37	4	15	17	11.765	45.946	1	16.357	1	57.813	3
C38	8	6	10	40.000	27.027	21	3.062	15	50.685	11
C39	9	11	14	42.857	37.838	4	16.328	2	60.656	1
C40	8	8	11	45.455	29.730	13	10.121	4	56.061	4
C41	6	10	11	45.455	29.730	15	3.572	13	50.685	10
C43	7	4	8	37.500	21.622	27	0.271	26	38.542	32
D44	3	2	3	66.667	8.108	37	0.000	37	34.579	37
D45	3	4	4	75.000	10.811	36	0.000	36	37.000	34
D46	2	2	2	100.000	5.405	38	0.000	38	30.081	38
Mean value	5.615	5.615	8.923	41.277	26.316	–	3.485	–	45.531	–

information integration level for ensuring epidemic prevention.

4.2. Analysis of the individual network characteristics

In Table 1, the poor performance of individual centrality in various industrial sectors is the main reason for the poor overall performance of the industrial sectors' IIN. The performance of degree centers shows that the number one railway, shipping, aerospace, and other transportation equipment manufacturing industry was very different from the number one water production and supply industry. The top three railway, shipping, aerospace, and other transport equipment manufacturers showed a serious imbalance between point of entry and point of exit. Especially upstream C31 of the industrial sectors' chain, this could bring about more innovation information spillover to the downstream industrial sectors. However, its point-out degree is only 1, while the point-in degree is 15. The power, heat, gas, and water production and supply industrial sectors (D44–46) were the worst performing. However, the strong information relationship accounts for a relatively high proportion, indicating that the related industrial sectors can achieve better two-way information spillover. As can be seen from the proportion of strong information relationship, except for D46, the proportion of strong information relationships in most other industrial sectors is relatively low. That is to say, the information relationship between most industrial sectors is one-way. III among industrial sectors is weak, and the driving effect of industrial sectors' information integration is poor.

With the rapid development of 5 G technology, the manufacturing sector needs to be incorporated into other industrial sectors through information and communications technology. However, in fourth place, its points-out degree is only two above the point-in degree. Of the 38 industrial sectors, only 14 are information-related. The two-way strong information correlation ratio accounts for only 42.857%, indicating

Table 2
The effect of industrial sectors' information integration plates.

Item	Plates	Number of reception relations				Number of members	Number of external relations of the receiving plate	Plate type
		Plate I	Plate II	Plate III	Plate IV			
Number of information overflow	I	54	9	0	0	11	15	Broker
	II	15	34	2	20	10	24	Main overflow
	III	0	5	92	9	14	2	Bidirectional overflow
	IV	0	10	0	4	3	29	Main benefit

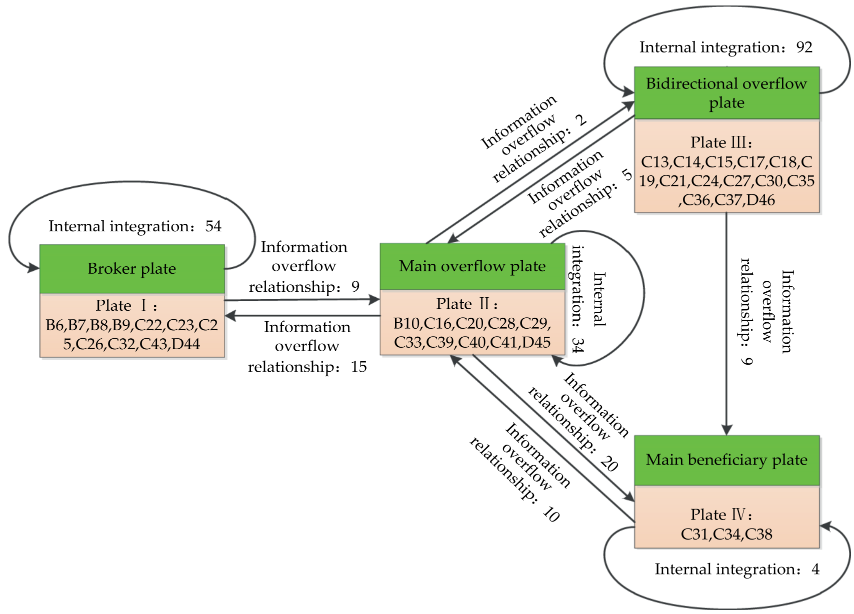

Fig. 6. Schematic diagram of interplate information spillover effect.

that China still faces many obstacles to achieve the goal of intelligent manufacturing through information and communications technology. It can be seen from the performance of betweenness centrality that C37, C39, and C31 rank as the top three, indicating that these industrial sectors are in the position of intermediary bridges in the IIN. By contrast, a total of five of the 38 industrial sectors had a betweenness centrality of 0. They are oil and gas extraction, agricultural and sideline food processing, and water production and supply, indicating that these five industrial sectors are on the edge of the IIN. The mean value of closeness is 45.531, and there are 19 industrial sectors above the mean value. This accounts for half of the total amount, which indicates that the information distance distribution between the IIN is relatively balanced, and the length of the accessible path between different industrial sectors does not differ much. The number one, C39, was most closely correlated with information integration in other industrial sectors.

According to the three aspects of individual network characteristics, C37, C31, C39, C30, and other industrial sectors are at the IIN core. The electricity, heat, gas, and water production and supply sectors were the worst performing, at the edge of the integration network. The performance of the pharmaceutical manufacturing sector, with high and equal point-in and -out degrees, is better than that of most industrial sectors. The betweenness centrality and closeness are both above average, which indicates that China can quickly successfully and respond to a new epidemic outbreak. Generally speaking, the level of the industrial sectors' IIN is not high in China, and the mode of strong information correlation between industrial sectors is relatively low. This results in the poor effect of industrial sectors' IIN.

In response to the COVID-19 outbreak, tools based on information and communication technologies such as health codes are used to prevent the spread of the epidemic. Supply chains in key fields such as next-generation information technology, high-end equipment manufacturing, and new materials have been greatly affected. On the one hand, the field of next-generation information technology has achieved rapid development. Platforms such as Douyin, Kuaishou, and Bilibili have become effective channels for spreading information such as epidemic science and prevention and control education. On the other hand, the information technology-related manufacturing sector is facing difficulties. Affected by the epidemic, some export-oriented enterprises face risks such as delivery difficulties and contract defaults. On the one hand, new products are used to meet the demand for epidemic prevention materials, such as treatment drugs, protective equipment, and testing reagents. On the other hand, the basic research capacity is weak, and there are cross-industry data barriers and other prominent problems. The leading enterprises in information and communications technology have not been negatively affected by the epidemic, and indeed have made contributions to epidemic prevention and control work. Enterprises such as Xuzhou Heavy Industry participated in the construction of Wuhan Huoshenshan and Raytheon Hospitals to help with epidemic prevention and control. Government departments need

Table 3
The effect of the network characteristics on network performance.

Model	**Model 1**	**Model 2**	**Model 3**
Constant	7.763*** (0.903)	10,899.700 (15,329.850)	4.342*** (1.557)
Point centrality	0.149 (0.200)	–	–
Betweenness centrality	–	686.255** (292.627)	–
Closeness	–	–	9484.832 (11,867.88)
Government support	−0.183*** (0.057)	−2930.029* (1522.157)	−2898.667* (1554.341)
Proportion of state-owned economy	−0.362** (0.206)	−7507.000 (5520.905)	−5393.035 (5508.871)
Proportion of private economy	0.436*** (0.153)	10,869.700*** (4143.946)	11,654.150*** (4182.409)
F	8.1***	6.13***	4.79***
R^2	0.074	0.013	0.010
Hausman	40.11***	17.40***	28.97***
FE/RE	FE	FE	FE

Note: "*", "**", and "***" mean significant at the levels of 10%, 5%, and 1%, respectively.

to strengthen policy support for those information areas that can promote the role of industrial association and industrial clusters. The aim of these measures is to form more influential industrial sectors' IIN to prevent and control infectious diseases like COVID-19.

4.3. Analysis of the block model

The clustering results show that plate I has a total of 11 members: B6, B7, B8, B9, C22, C23, C25, C26, C32, C43, and D44. Plate II members (a total of 10) are B10, C16, C20, C28, C29, C33, C39, C40, C41, and D45. Plate III members (a total of 14) are C13, C14, C15, C17, C19, C18, C21, C24, C27, C30, C35, C36, C37, and D46. Plate IV members (a total of three) are C31 microcomputer, C34, and C38.

As can be seen from Table 2 and Fig. 6, the information spillover effect between plates is weak, and most of the information correlation exists within plates. Plate I only interacts with plate II, receiving 15 information resources. Plate II has 9 information resources as both the receiving and the issue number. The mining industrial sector is almost all located in this sector, and most industrial sectors are in the upstream of the industrial chain. The other plates are all correlated with each other in terms of information. The internal information relationship in plate II is 34 information resources, and the other plates received by the plate II correspond to 37 information resources. This indicates a strong bidirectional information spillover. The major industrial sectors are the materials and information technology sectors, which are the main driving force of the industrial sectors' IIN. The number of sending relationships in plate III was 14 information resources, which was significantly more than the number of receiving relationships. It has the largest number of members, mainly in the pharmaceutical sector and equipment manufacturing sector. The number of plate IV received relationship was 29 information resources, but its information overflow relationship was for only 10 information resources. This is less than the number of relations received from other plates, in line with the main beneficiary plate characteristics.

According to industrial planning, the key industrial sectors to be focused on in the future include the information revolution, intelligent manufacturing, biotechnology, green manufacturing, and other important industrial sectors that generate momentum for industrial sectors' information integration. As can be seen from Fig. 6, computer, communications, and other electronic equipment manufacturing; automobile manufacturing; medicine manufacturing; special equipment manufacturing; and instrument manufacturing are all located in the information overflow sectors. However, compared to the number of internal information relationships, the information spillover effect to the outside of the plate is not good. The inter plate information integration effect still needs to be strengthened.

In response to COVID-19, III tools such as artificial intelligence, big data, industrial Internet, and cloud computing are playing a role in virus research, prevention and control measures, vaccine development, and epidemic information dissemination. Practical input and digital integration, through the development of digital platforms and specialized applications, open digital infrastructure, and algorithmic capabilities, provide a solid foundation for the fight against the epidemic. However, there are still some deficiencies in core technologies and industrial systems, such as weak safety awareness, insufficient technology innovation, and incomplete system construction. To address these shortcomings, an open, innovation-driven 5 G technology system should be applied to the innovation of technology, products, and business models, and serve the governance of public health practices. In addition, a 5 G technology system should be embedded into other industrial sectors to realize information linkage in industrial fields like technology, business, products, etc. Government departments should take the lead in using online and cloud-based technologies and providing more favorable policies in terms of investment proportion and credit support.

4.4. Analysis of the effect of the network characteristics on network performance

In Table 3, although point centrality and closeness have significant positive effects on IIN performance in terms of random effects, the Hausman test supports a fixed effect.

According to Model 1, the point centrality has a positive effect on IIN performance, but the result is not significant. The point centrality of industrial sectors may have a positive effect on IIN performance. However, the unreasonable information connection mode of the integration network creates a serious imbalance. The industrial sectors in the upstream of the industrial chain have no significant effect on the industrial sectors' information integration of the downstream sectors. However, the positive relationship indicates that the industrial sectors can try to establish more information technology-related channels with upstream and downstream and related industrial sectors. Doing so can enhance the point centrality and balance the relationship between the degree of input and the degree of output to enhance the linkage effect of information integration between industrial sectors.

According to Model 2, the betweenness centrality has a positive influence on the IIN performance, and the result has significance above 5%. The betweenness centrality can positively improve the IIN performance. The industrial sectors on the edge of the IIN need to actively expand the upstream and downstream business and improve their position as an information bridge in the industrial chain. The industrial sector needs to improve the performance of its own industry indirectly through the IIN of adjacent industrial sectors.

According to Model 3, the closeness to the center has a positive effect on IIN performance, but it also fails to pass the significance test in the fixed-effects model. This suggests that an increase in closeness may increase the IIN performance. The improvement of closeness can shorten the information integration distance of various industrial sectors and eliminate the cost of information technology convergence. However, due to the large industry barriers between various industrial sectors in the current IIN, the information integration effect of industrial sectors is not ideal. More marginal industrial sectors is why the fixed effects model is not significant.

As a sudden exogenous shock, the outbreak and spread of COVID-19 has caused widespread concern and significantly reduced the scale of various production activities. To a large extent, COVID-19 restricts the development of industrial sectors' information integration activities. There is no doubt that the COVID-19 epidemic is an important test of China's industrial sectors' information integration capacity. The following measures should be taken to solve the above problems. How the industrial system supports the development of the social security system and biosafety system should be explored to make up for the shortcomings in the existing industrial sectors' IIN. Information technology innovation and entrepreneurship should be strengthened to explore new forms of industrial sector information integration. Industrial sectors' IIN should be strengthened to establish the industrial sector and health sector collaboration mechanism. A tolerant and open institutional system and policy environment should be improved to encourage technology innovation such as the Internet of Things, big data, artificial intelligence, and cloud computing. Policies such as priority review, patent compensation, and data protection for drug trials should be formulated to speed up the development of new drugs for epidemics such as COVID-19.

5. Conclusions and implications

To respond to COVID-19, it is essential to promote industrial sectors' information integration. The study introduced the idea of the gravity mode to study the sector information distance variable and construct the industrial sectors' IIN. The overall trend, individual characteristics, and block model of the industrial sectors' IIN were analyzed. On this basis, we further studied the influence of the current state of the network characteristics on the IIN performance. The study has important significance. The study is helpful to grasp the changing laws and trends of information integration within industrial sectors and respond to changes in COVID-19 prevention and control. The study provides a basis for industrial sectors' IIN governance, and improves IIN performance. In addition, this study not only helps to clarify the underlying mechanism by which COVID-19 affects industrial sectors' information integration, but also has important practical significance for improving the level of IIN for public health governance.

The results of this study are as follows. (i) The overall density of industrial sectors' IIN fluctuates. It has shown a downward trend in the past two years and reached its lowest level in 2018. The network efficiency presents a slow rising trend, and the overall IIN stability is poor. Although the rigid hierarchy of industrial sectors is gradually breaking down, the overall closeness of the information integration network needs to be strengthened. (ii) The railway, shipbuilding, aerospace, and other transportation equipment manufacturing sector, as well as the computers, communications, and other electronic equipment manufacturing sector are at the heart of the industrial sectors' IIN. Electricity, heat, gas, and water production and supply sector have the worst performance in three dimensions in the edge of the network. Most industrial sectors have a one-way, weak information correlation, and the effect of industrial sectors' information integration is not obvious. The information spillover effect of industrial sectors in the upstream of the industrial chain is poor, and it is difficult to have a strong effect on the downstream industry. (iii) Most of the plates belong to the interplate effect. The information linkage effect is poor, especially for the first plate, with only a plate II information overflow relationship. Plate II is at the core of the industrial sectors' IIN, while the network with plate III provides information overflow to the main engine. (iv) The individual betweenness centrality has a significant positive effect on the IIN performance. Although point centrality and closeness have positive effects on the network performance, they are not significant.

The implications for the development of industrial sectors' IIN and their response to public health events such as COVID-19 are as follows.

While focusing on the development of key areas, we should also clearly recognize the loose structure of the industrial sectors' IIN. The government should actively explore new channels of industrial sectors' information integration, and set up an information integration platform through multiple pathways. In addition, the government should not only promote the information integration of the upstream industry through the downstream industry, but also force the downstream industry to improve the industrial sectors' IIN via two-way strong correlations. The information linkage effect within and between plates should be taken seriously to improve policy development. The government should act on the main information spillover sector and the two-way information spillover sector by formulating targeted industrial policies. In particular, the government should actively strengthen the information bridge function and promote the development of industrial sectors' IIN.

In the context of industrial sectors' coordination, the industrial sectors should not only enhance emergency response and coordination in the industrial chain and supply chain, but should also establish a digital supply chain warning system based on emergencies and identify risks. Tools based on information and communication technologies such as health codes should be widely used to prevent the spread of the epidemic. The government should provide more favorable policies in terms of investment proportion and credit support for effective prevention and control of epidemics such as COVID-19. A tolerant and open institutional system and policy environment would encourage technology innovation such as the Internet of Things, big data, artificial intelligence, and cloud computing. In addition, policies such as priority review, patent compensation, and data protection for drug trials should be formulated to speed up the development of new drugs for epidemics such as COVID-19.

Although this study has made some important contributions, it also has some shortcomings. The improvement of this industrial sectors' IIN is not explored in depth in the study. How the IIN can be optimized should be the focus of future research on epidemic prevention and control. In addition, the networks in different countries and between countries should be studied through the fuzzy set method.

CRediT authorship contribution statement

Shi Yin: Conceptualization, Resources, Writing - original draft, Writing - review & editing, Supervision. **Nan Zhang:** Methodology, Investigation, Writing - original draft, Visualization. **Hengmin Dong:** Methodology, Investigation, Visualization.

Declaration of Competing Interests

None

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