

## Retraction

# Retracted: Factors Affecting the Evolution of Advanced Manufacturing Innovation Networks Based on Cloud Computing and Multiagent Simulation

## Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

- [1] W. Jianbo and X. Cao, "Factors Affecting the Evolution of Advanced Manufacturing Innovation Networks Based on Cloud Computing and Multiagent Simulation," *Mathematical Problems in Engineering*, vol. 2021, Article ID 5557606, 12 pages, 2021.

## Research Article

# Factors Affecting the Evolution of Advanced Manufacturing Innovation Networks Based on Cloud Computing and Multiagent Simulation

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Facing the pressure of low-cost competition brought by the homogenization of commodities, the manufacturing industry seeks to survive by providing services. By providing outsourcing of value-added services to date, we are focusing on innovation in our business model. With the advancement of science and technology, manufacturing innovation is facing higher challenges, especially the popularization of the Internet, which makes the manufacturing industry have to move closer to new industries. Based on cloud computing, this paper conducts a multiagent simulation on the evolution factors of the innovation network of advanced manufacturing. This article takes three types of simulation subjects: evolutionary network, manufacturing (cluster), and innovation evolution system as the research objects. The factors affecting the evolution of the research are innovation resources, innovation opportunities, innovation desire, innovation pressure, relationship strength, network scale, and network scope. Network differences carry over variable indicators and analyze quantitative regression indicators and then build a research model. The research results show that the average conversion efficiency of the manufacturing industry (0.523) is significantly lower than the average R&D innovation efficiency (0.725), which to a certain extent indicates that the manufacturing industry still has weak links in the export conversion stage at the back end of the innovation value chain. Some of the companies may have problems such as low ability to transform scientific and technological achievements and insufficient export competitiveness of high-tech products, which to a large extent affects and restricts the improvement of manufacturing export transformation efficiency.

## 1. Introduction

With the in-depth implementation of the national innovation-driven development strategy, R&D innovation and industrial transformation and upgrading activities have received increasing attention from government departments at all levels. The construction of the national manufacturing industry aims to support a large number of high-tech enterprises in the park to carry out R&D and innovation activities to form a high-quality growth pole driven by knowledge and innovation and to promote regional industrial upgrading and economic transformation. After years of development, the current national manufacturing

industry has become the main force in promoting the implementation of the national innovation-driven development strategy.

Bui N begins the research on organizational innovation, the organizational structure shifts from a purely hierarchical system to a functional system, the business division is formed as the main form of organizational innovation, and then the organizational structure evolves into a super business division, and the organization, it layers the foundation for the evolution of the structure [1]. Suh et al. proposed three major factors affecting organizational innovation and studied the changes in new organizational forms, which is a preliminary exploration of the factors

affecting organizational innovation [2]. Benzaoui proposed that organizational innovation is a planned change in organizational structure and organizational division of labor. Organizational innovation enhances the creativity of organizational operations and highlights the impact of organizational structure and technological innovation on organizational innovation. At this stage, the influencing factors of organizational innovation are deeply explored [3]. From the perspective of cloud computing technology and cross-organizational communication, Mohammadi explores the development of innovative activities of enterprises in different organizational configurations. At this stage, it studies the changes in organizational innovation forms and influencing factors from the perspective of technical knowledge [4]. Dayarathna et al. found that the influence of organizational green learning, environmental protection, public opinion pressure, and leadership awareness is gradually increasing. Enterprises should respond to national policies, adapt to environmental changes, and promote organizational innovation [5].

Armbrust et al. found that the impact of culture on organizational innovation is reflected in both positive and negative aspects. Transactional leadership and organizational climate stimulate employees' willingness to innovate and promote organizational innovation [6]. Sanderson found that the influence of organizational collaboration and openness on organizational innovation is in a dynamic cycle and is affected by organizational dependence, and the relationship between the two needs to be reasonably grasped [7]. Oliver combines organizational structure with resources and proposes that companies should formulate organizational strategies, optimize the relationship between organizational structure and resources, and promote organizational innovation [8]. Danwitz found that big data technology plays a regulatory role among knowledge transfer, organizational proximity, and innovation performance, and knowledge management plays an intermediary role in organizational innovation. Enterprises should establish learning organizations to promote organizational innovation. To sum up, most of the current research on the influencing factors of organizational innovation tends to be scattered, and there is a lack of research on the influencing factors and mechanisms of organizational innovation in the era of big data. For this reason, this paper uses the combination weighting method and the ISM system to analyze the main influencing factors and influencing mechanism, and taking red-collar enterprises as an example, expounds the feasibility of the influencing mechanism [9]. Ward et al. proposed to build a cloud framework based on the SaaS platform and complete the design after cloud computing users' selection of the environment [10].

Based on cloud computing, this paper conducts a multiagent simulation on the evolution factors of the innovation network of advanced manufacturing. This article takes three types of simulation subjects: evolutionary network, manufacturing (cluster), and innovation evolution system as the research objects. The factors affecting the evolution of the research are innovation resources, innovation opportunities, innovation desire, innovation

pressure, relationship strength, network scale, and network scope. Network differences carry over variable indicators and analyze quantitative regression indicators, and then build a research model. Based on this, in order to better explore the internal development and evolution of knowledge topics and make up for the lack of traditional prediction methods in the prediction of knowledge topics, this article focuses on two major issues in the evolution of knowledge manufacturing innovation network prediction research: multiagent influence factors and sensitivity to network evolution.

## 2. Evolutionary Prediction Model

**2.1. Cloud Computing-Based Manufacturing Evolution Prediction Model.** The current evolution of innovation is trending towards large-scale and massive development, and a single support vector machine is ineffective in obtaining the prediction result of the evolution of the manufacturing industry within a valid time. For this reason, the advantage of the parallel processing problem of the cloud computing platform is adopted, parallel modeling to realize manufacturing evolution prediction. The specific principle is to assign each subset to a node of the cloud computing platform through the cloud computing system, use the support vector machine to build the modeling on each node, and then use the cloud computing system to calculate the modeling results of each subset, perform fusion and aggregation to form a powerful innovation evolution prediction model, and output the final prediction results of innovation evolution prediction [11].

In the field of cloud computing, the requirements for the stability of the cloud framework have become more stringent. To save the cost of cloud computing and strengthen the robustness of the server itself, the need for cloud framework stability design arises. As a state-of-the-art technology emerging rapidly today, cloud computing frameworks use group computing to connect many individual computers over high-speed local area networks for high computing efficiency and capability [12]. To a certain extent, this technology can connect computer and data calculations in series, transforming hardware support into software support. It also has the characteristics of real-time dynamics and strong adaptive ability, and the excellent framework integration mechanism can more perfectly fulfill user requirements [13]. Since the cloud computing framework was proposed, the development of this technology has been particularly rapid in the field of cloud computing. The service method of the cloud computing framework: It is based on a series of methods such as aggregation, improvement, and resource management of the data network to meet its specific needs. The cloud framework can also be divided according to the size of the space [14]. Small-scale cloud computing framework: It means that on the basis of IT, equipment, instructions can be completed according to requirements [15]. In a large-scale situation, it will go through a well-built computer service cluster and make full use of the Internet method to achieve the required command services [16]. When the cloud computing framework meets

the current network conditions, the network data resources will be free to use and will not be restricted due to conditions, and users can use this service at any time and place [17]. However, due to the ubiquity of Internet users and the decentralization of data, the current cloud frameworks face more diversified problems. How to effectively control these problems is a problem that needs attention in the current cloud framework research field [18]. At present, relevant scholars have also proposed some better methods for the cloud framework, but there are also some problems. The more typical methods are as follows:

$$\theta = -\frac{1}{T} \ln(1 + \beta), \quad (1)$$

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{t=1}^{n_j} \sum_{r=1}^{n_h} |y_{ij} - y_{hr}|}{2n^2 u}$$

To a certain extent, the framework can greatly improve the timely response rate of executing instructions and fully meet the basic requirements of users as much as possible, with high stability coefficient and excellent reliability. However, this framework has the problems of low efficiency, low reliability, and unsmooth network operation in the actual complex data calculation [19]. In response to the above problems, this paper proposes a high-elastic cloud architecture design method for cloud computing networks and analyzes its reliability [20]. Experiments prove that the cloud framework has high flexibility, stable data flow, accurate and rich information, and high-quality reliability.

**2.2. Manufacturing Innovation Network Evolution Method.** Among the advanced manufacturing innovation network evolution analysis methods, the discrete-time method is the most used. This type of method divides the corpus set before extracting the topic. It is more dependent on the structure of the corpus, and the results obtained are greatly affected by the division method. And it is necessary to confirm the same theme on different subsets. That is, after getting the theme of each period, the theme is related according to the similarity of the words or the overlap of the articles under the theme. The accuracy of the theme alignment is difficult to guarantee [21]. Introducing time information into the evolution model means directly introducing time information into the topic model, such as DTM (Dynamic Topic Models), TOT (Topic Over Time), and other models. DTM can describe the changes in the word distribution of a topic over time. TOT will be regarded as a continuous distribution on the time label; there are problems of time dispersion and granularity that are difficult to control, and the above methods assume that the topic set at each period is constant, which is inconsistent with reality. The literature may be a new topic that has not appeared in the previous period. The postdiscrete-time method is to first perform topic extraction, find the time label of each document through the clustering of the documents under the topic, and then match the time label with the topic to form a “time-topic” matrix. This method is avoided in order to solve the problem of topic alignment in the discrete-time method. Researchers only need to mark the

topic with time in the follow-up [22]. At the same time, the postdiscrete-time method allows the death of old themes and the emergence of new themes, which is more in line with the actual situation of the evolution of manufacturing innovation networks. In addition, in recent years, another trend in research on the evolution of innovation networks in advanced manufacturing is to use structural information in the scientific research literature, such as author information and citation information, to explore the evolution of knowledge topics over time, but related research results are still relatively few and have not reached the level of practicality; most of the evolution methods lack fine-grained, deep-level content foundation, and the evolution effect needs to be improved. Divided according to the evolution mode of the theme, it can also be divided into three modes: intensity evolution, content evolution, and structural evolution [23]. Strength evolution represents changes in topic strength through several indicators that can reflect the strength of the topic, such as the number of documents associated with the topic, the degree of attention of the document, and the probability of feature words under the topic [24]. Content evolution is mainly to study the differentiation and fusion between themes in the process of time change. It is generally based on the association between themes, and the cooccurrence matrix between themes is used as a transition matrix to simulate the natural selection phenomenon of species evolution in biology. The related explanation of life cycle theory describes the process of the subject's emergence, development, maturity, and extinction, and finally uses the dissipative structure theory, dynamic model, or infectious disease model to explain [25]. Structural evolution is the use of some structural information contained in the topic to construct a network with certain attributes, such as the use of authors or institutions to map the topic cooperation model or the use of similarity between topics to construct a similarity matrix to explore the evolution of the network structure over time. The specific description may include network centrality, density, small world, and other attributes that can reflect the network structure, involving theoretical knowledge such as complex networks and knowledge graphs.

**2.3. Forecasting Method Research.** The evolution of the manufacturing innovation network is not the end, but the evolution will be further expanded. This article hopes to predict the future development of the theme. Researchers are based on different theoretical foundations. Qualitative methods include analogy, but qualitative analysis is often limited by subjective judgments. Quantitative methods are more scientific. Common methods include link prediction, autoregressive models, gray models, and Markov. These models have the ability to predict development trends and can confirm the law of evolution of things to a certain extent. Among them, the research of the Markov model started the earliest and has a rich theoretical foundation. The Gray model emerged after 1990 and has the widest application field. In recent years, the research process of domestic and foreign scholars applying this model can be divided into the

following parts: determining the evolution time and period, selecting the evolution index, calculating the state transition probability, and analyzing the evolution results. The application direction is divided into two categories. One is to use the first-order and finite nature of Markov chains to predict the limit probability. By calculating the one-step transition probability, the  $n$ -step stable transition probability is given, and the limit probability in the steady state represents the total research of the development trend of the system. One type is the analysis of Markov chains combined with multivariate time series, that is, forecasting based on the changing trend of internal structural factors of things, focusing on the exploration of micromechanisms. In addition, the Markov model is also embedded in the DPS software, which makes the application analysis of the Markov chain more extensive. As an extension of the Markov model, HMM is widely used in various prediction tasks, such as public opinion propagation prediction, stock prediction, attack prediction, and behavior prediction. In addition, the model also has applications in text classification, manufacturing, innovation network evolution, automatic speech recognition, and fault diagnosis. Through the analysis of the current research status of evolutionary prediction methods, it can be seen that the existing research is mostly the evolution of the subject content, intensity, and structure, and there is less research on the evolution relationship and steady-state distribution of the subjects in the field and quantitative prediction of knowledge topics. There is also less research. Based on the influencing factor index system constructed above, the scoring results are weighted and averaged to obtain the fuzzy complementary matrix  $R$  of each influencing factor, and according to the formula:

$$u_h \leq u_j \leq \dots \leq u_k,$$

$$G_{jj} = \frac{(1/2u_j) \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{jr}|}{n_j^2}, \quad (2)$$

$$Gw = \sum_{j=1}^k G_{jj} p_j s_j.$$

Calculate the weights of primary and secondary indicators  $Gw$ . Then, based on the data obtained from the survey, the average value of the top five industry results is selected, and the index is calculated according to the following formula  $G_t$ :

$$\ln\left(\frac{\text{FI}_{it}}{\text{FI}_{it} - 1}\right) = \alpha + \beta \ln \text{FI}_{it} - 1 + \phi X_{it} - 1 + v_i + \tau_t,$$

$$k_{t1}[i] = \sum_j \cos(w_i^1, w_j^2), \quad (3)$$

$$G_t = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} (1 - D_{jh}).$$

Then, combine the weights according to the following formula to obtain the combined weights of first and second

indicators  $D_{jh}$  And the ranking of organizational innovation factors:

$$D_{jh} = \frac{d_{jh} - P_{jh}}{d_{jh} + P_{jh}},$$

$$d_{jh} = \int_0^\infty dF_j(y) \int_0^y (y - x) dF_h(x), \quad (4)$$

$$P_{jh} = \int_0^\infty dF_h(y) \int_0^y (y - x) dF_j(y).$$

The primary indicators that affect organizational innovation are technology and knowledge, organizational structure and strategic characteristics, organizational learning, knowledge flow, and information technology. At the same time, to explore the logical relationships of the main influencing factors, select the top 80% of the secondary indicators as the main influencing factors, and further analyze the influence mechanism between the factors:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N k\left(\frac{X_i - x}{h}\right),$$

$$k(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right), \quad (5)$$

$$h_t = \tanh(w_c x_t + u_c(r_t \Theta h_{t-1}) + b_c),$$

$$h_t = z_t \Theta h_{t-1} + (1 - z_t) \Theta h_t.$$

The addition of undesired output indicators overcomes the problems caused by radial and angle, making the evaluation results more in line with reality and more accurate. The construction model is as follows: Suppose there are  $n$  decision-making units, and their input and output matrices are as follows:

$$\sigma t = \frac{\sqrt{(1/n) \sum_{i=1}^n (\text{FI}_{it} - \bar{\text{FI}}_{it})^2}}{\bar{\text{FI}}_{it}}, \quad (6)$$

$$u_{(j|i)} = w_{ij} A_i,$$

$$s_j = \sum_i c_{ij} u_{(j|i)}.$$

The coding adopts a binary coding method, assigning a value of 1 to the selected subset and assigning a value of 0 to the unselected subset, then any problem solution can be represented by a set of binary codes, that is, a queue. This coding method is also convenient for the later selection, crossover, and mutation operations to search for solutions to problems, among them  $c_{ij}$  is the weight variable:

$$\ln\left(\frac{\text{FI}_{it}}{\text{FI}_{it} - 1}\right) = \alpha + \beta \ln \text{FI}_{it} - 1 + v_i + \mathfrak{s}_t, \quad (7)$$

$$c_{ij} = \frac{e^{b_{ij}}}{\sum_k e^{b_{ik}}}.$$

### 3. Design of Manufacturing Innovation Network Evolution Model

**3.1. Network Evolution Model.** The main body of simulation in this paper is divided into three categories: evolutionary network, manufacturing (cluster), and innovation evolution systems. When using the fuzzy analytic hierarchy process, the data is collected by issuing questionnaires to company leaders with innovative management experience and comparing and scoring the influencing factors of various indicators according to the 0.1–0.9 scale method. In addition, for asset input in the following year, the total assets of the manufacturing industry at the end of the previous fiscal year are selected, and the total number of personnel in the manufacturing industry at the end of the previous fiscal year is selected as personnel—input for the next year. The output of the second stage uses the indicator of total manufacturing exports. Factors that influence the evolution of research are innovation resources, innovation opportunities, innovation desires, innovation pressures, the strength of relationships, network size, network scope, and network differences.

#### 3.2. Network Evolution Model Construction and Evaluation

**3.2.1. Model Construction.** The DEA method can establish performance benchmarks by evaluating the efficiency of decision-making units and help decision-makers find shortcomings that affect performance improvement, which is conducive to improving and enhancing the performance of decision-making units. Judging from the efficiency measurement of the existing DEA methods, the traditional DEA treats the decision-making unit as a whole and only measures its operational efficiency through input and output data. It does not fully consider the internal operation process of the decision-making unit, so it is difficult to comprehensively and systematically analyze the innovation activity process of the decision-making unit. Based on the multistage and nonlinear characteristics of advanced manufacturing R&D innovation and export transformation activities, this paper intends to use a two-stage dynamic intertemporal DEA model to analyze the manufacturing industry's R&D innovation, export transformation, and overall efficiency. In the construction of the two-stage DEA model, it is further extended to a dynamic model. That is, the periods are linked together by cyclic activities, which is called the dynamic interperiod DEA model. This paper adopts the dynamic intertemporal two-stage comprehensive model proposed by Xiong et al. to construct the analysis framework. This article assumes that the first stage (R&D and innovation stage) and the second stage (export conversion stage) are of equal importance, so the weights are set to 1/2 in advance. That is, the overall efficiency is defined as the weighted average sum of the efficiencies of the two substages:

$$\begin{aligned} \theta_0^t &= \min \frac{1}{2} \theta_{10}^t + \frac{1}{2} \theta_{20}^t, \\ c_{ij} &= \frac{e^{b_{ij}}}{\sum_k e^{b_{ik}}}. \end{aligned} \quad (8)$$

Advanced manufacturing is an important carrier for regional innovation activities, but the traditional two-stage DEA model is a single-period static model and cannot measure interperiod dynamic changes. From the perspective of manufacturing R&D innovation and export transformation activities, it has the characteristics of dynamic intertemporal.

**3.2.2. Carryover Variable Indicators.** Since the innovation value chain process is a dynamic interactive process, the back-end activities of this period will also have an impact on the front-end activities of the next period, so this article considers adding carryover variables. The carryover variable in the first stage is the stock of patent knowledge. The reason for adopting this carryover variable is that the patents generated in the current year will be included in the knowledge stock at a certain depreciation rate and will affect the knowledge production activities in the next year. On the one hand, patents will form knowledge accumulation over time, which will act as a knowledge pool for the production of new knowledge in the following year. On the other hand, new knowledge will continue to be produced. New knowledge produced in the past will gradually be depreciated. We need to consider the depreciation of knowledge. Drawing on the experience of previous studies, the depreciation rate of knowledge is calculated using a depreciation rate of 15%. In the selection of carryover variables in the second stage, this article uses the indicator of total manufacturing exports multiplied by a fixed ratio. The reason for adopting this carryover variable is that, on the one hand, the company will use part of the total export value of the current year for the following year's export trade expenditures and export conversion incentives. On the other hand, the company will invest part of the total export value according to the export situation. The first phase of export transformation forms a virtuous circle of export transformation. Therefore, this stage adopts the carryover variable of total exports multiplied by a fixed ratio (10%).

**3.2.3. Selection of Econometric Regression Indicators.** To analyze the relevant factors affecting the R&D innovation, export transformation, and overall efficiency of advanced manufacturing from the perspective of innovation-driven, this paper selects relevant control variable indicators from the three perspectives of the manufacturing external environment, internal conditions, and innovation value chain. The external environment includes four indicators: city technical level, city economic level, city openness, and geographic distance. The city's technology level (S&T) is measured by dividing the city's annual science and technology expenditure by the city's annual fiscal expenditure, the city's economic level (Eco) is measured by the city's per capita GDP, and the city's openness is measured by dividing the city's annual foreign direct investment by the city's current GDP measured, geographic distance (Dist) is measured by the straight-line distance of each city from the nearest coastline, and this indicator is obtained using Google Maps. The internal conditions of the manufacturing industry

include two indicators: human capital and debt financing. Human capital ( $H_r$ ) is measured by the number of employees with a college degree or above in each manufacturing industry, and debt financing ( $D_f$ ) is measured by dividing the year-end liabilities of the previous year by the year-end assets. The innovation value chain index selects the efficiency value ( $E_2$ ) in the R&D and innovation stage and uses this indicator to return the efficiency value in the export transformation stage. This is also a key indicator to analyze the impact of R&D and innovation on export transformation from an innovation-driven perspective.

## 4. Influencing Factors on Evolution of Advanced Manufacturing Innovation Network

**4.1. Evolution Factors of Multiagent Networks.** To grasp the law of innovation evolution system confrontation from the perspective of multiagent simulation, the evolution evaluation index is based on the overall emergence in the simulation process, rather than the simple correlation between the cycle length of each loop and the evolution result. In the overall evolution process, the information advantage is reflected in the amount of target information and the average acquisition time; the determination effect is reflected in the accurate determination of the target threat information and the average determination time, and the decision advantage is reflected in the accuracy of the decision and the average decision response time, and action advantage is reflected in the number of effective strikes completed and the average strike time. Since this model does not set legal targets and does not distinguish between general frequency bands, special frequency bands and procedures, and visual manufacturing targets for flight control, it does not involve the index analysis of decision-making accuracy.

As shown in Figure 1, political factors include political requirements and social responsibilities. The former refers to the state and government's rigid requirements for the implementation of relevant policies and spirit of enterprises, while the latter refers to the social obligations undertaken by enterprises that are higher than their own goals. The former is passive, while the latter emphasizes proactive behavior. Both help companies maintain relationships with stakeholders such as the government and partners and further help companies obtain innovation resource support, thereby promoting platform innovation. For example, most of the decisions in the development of Wanda can be combined with the latest party and government policies. Only by knowing what your country needs can you guide your company in that direction (political requirements — platform innovation).

As shown in Table 1, dynamic capability is the ability of an enterprise to adapt to a rapidly changing complex environment. It also emphasizes that enterprises can grasp the development opportunities brought about by environmental changes through the reconfiguration of resources and skills. It includes four dimensions: integration capability, technical capability, absorptive capacity, and organizational forgetting. Here, organizational forgetting is used as an example to illustrate the impact of platform innovation. At the same

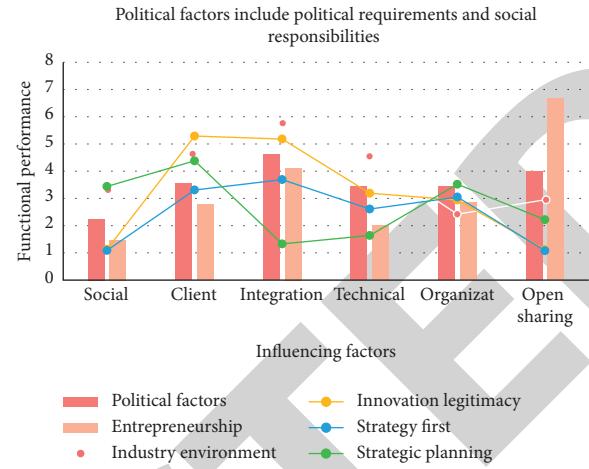


FIGURE 1: Political factors include political requirements and social responsibilities.

time, according to the calculation results, the average manufacturing conversion efficiency (0.523) is significantly lower than the average R&D innovation efficiency (0.725), which to a certain extent indicates that the manufacturing industry still has weak links in the export conversion stage at the back end of the innovation value chain. Internal enterprises may have problems such as low ability to transform scientific and technological achievements and insufficient export competitiveness of high-tech products, which to a large extent affects and restricts the improvement of manufacturing, export, transformation efficiency.

As shown in Figure 2, the industry environment includes policy orientation, environmental changes, and the degree of competition. To illustrate the impact of platform innovation, we will only take environmental changes as an example. Environmental changes are the most active and uncontrollable factor, and corporate strategies must be continuously adjusted to environmental changes. As shown in Table 2, this change will prompt enterprises to carry out reforms and innovations. For example, the continuous change of the economic and financial landscape and the large changes in the economic situation will prompt CCB to carry out platform innovation and transformation.

As shown in Figure 3, market demand includes customer needs and social pain points. The former is based on a microperspective, while the latter has an impact on platform innovation from a macro level. The “demand leads to innovation” theory believes that the stronger the customer demand, it will drive the enterprise to innovate and promote the growth of the enterprise. For example, Haier’s “big enterprise disease” blocked customer demand and made enterprise production and user demand farther and farther away, while the innovation of the “Rendanheyi” platform made “the enterprise borderless” and narrowed the distance between the enterprise and the customer.

The corporate strategy includes three dimensions: strategic advancement, strategic planning, and strategic flexibility. Here, only strategic precedents are used to illustrate the impact of platform innovation. As shown in Figure 4, the advanced strategy will enable companies to

TABLE 1: Dynamic capability is the enterprise adapting to rapid changes.

Item	Industry environment	Political factors	Entrepreneurship	Innovation legitimacy	Strategy first	Strategic planning
Social	3.31	2.25	1.48	1.13	1.09	3.44
Client	4.67	3.56	2.77	5.29	3.31	4.38
Integration	5.78	4.61	4.12	5.18	3.69	1.33
Technical	4.54	3.45	2	3.19	2.61	1.64
Organizat	2.42	3.45	2.84	2.94	3.05	3.52
Sharing	2.95	4	6.67	1.12	1.08	2.22

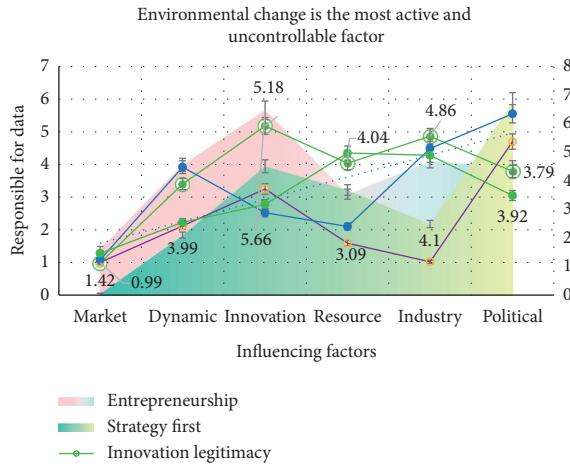


FIGURE 2: Environmental change is the most active and uncontrollable factor.

establish long-term development visions and innovation plans and promote companies to carry out innovative practices. Platform innovation is strategically oriented and requires the guidance and support of advanced strategies.

Innovation culture includes three dimensions: active collaboration, open sharing, and innovative atmosphere. As shown in Table 3, we only take the innovation atmosphere as an example to illustrate the impact of platform innovation. An innovative atmosphere refers to the common perception of innovation-related factors in the work environment among employees within an enterprise. When employees feel that the enterprise supports platform innovation more strongly, their enthusiasm and innovative behavior increase, and the enterprise's platform innovation capability becomes stronger. The case companies have a good atmosphere for innovation. In interviews, CCB frequently holds creative salons and maker contests to collect ideas for different products from employees, providing mentors and long-term tracking for good creative incubation. Three ideas related to the "Three Strategies" incubate new products and market them. Another example is that Haier's innovative atmosphere is very strong. "Everyone can become a CEO" has inspired many entrepreneurs who lack resources and relationships to start their own business on the Haier platform.

Entrepreneurship factors are shown in Figure 5. Entrepreneurship is an innovative behavior. This study divides it into three dimensions, namely, the discovery of opportunities, courage to change, and belief and confidence. Here, we only use the discovery of opportunities as an example to illustrate the impact of platform innovation. As Meituan

Wang Xing said, "Entrepreneurship is the willingness to discover and pursue opportunities." Successful discovery and conversion of opportunities into practice will promote the development of enterprise platform innovation.

**4.2. Sensitivity Analysis of Manufacturing Innovation Network Evolution.** To further analyze the model, this paper uses MATLAB numerical simulation to determine the sensitivity of the number of users to changes in platform profit, to determine the factors that affect the platform profit the most, and to adjust the factors in conjunction with the pricing model to maximize platform profit. Suppose the simulation conditions are shown in Table 4.

As shown in Figure 6, in terms of output in the R&D and innovation stage, although patents are used as a proxy variable for R&D activities, there are certain shortcomings, but patents are an important content of knowledge and an important indicator of innovation output. In the relevant empirical analysis of R&D activities, scholars use the number of patent applications as the proxy variable of R&D output. At the same time, in view of the fact that invention patents have the highest gold content in patents and can better reflect innovation and knowledge, this paper selects the index of invention patent applications as a measure of R&D output. In terms of investment in the second stage, the export transformation stage, on the basis of the main case, continues to compare and analyze the follow-up cases to make the conclusions more comprehensive and objective.

Platform innovation is a destructive business model innovation. If you do not actively discard outdated thinking and inherent traditions, the reform will not be thorough and the innovation will not be effective. As shown in Figure 7, when analyzing the network evolution model in this study, the simulation curve basically reached theoretical saturation, and no new aspects appeared. We tested our conclusions using the following cases and finally found that the categorical code obtained in this study had good theoretical saturation. After revising and integrating the conceptual categories obtained from the analysis of all case data, the final result is obtained, as shown in Table 5.

As shown in Figure 8, when innovation resources are insufficient, the motivation for enterprise platform innovation will decrease. This research divides resource adequacy into three dimensions: human capital, social network, and performance basis. Here, the social network is used as an example to illustrate the impact of platform innovation. Social network refers to the formal or informal relationship link between an enterprise and related external institutions. As shown in Table 6, the social network relationship formed

TABLE 2: The economic and financial landscape is constantly changing.

Item	Entrepreneurship	Innovation legitimacy	Strategy first	Strategic planning	Social pain points	Client needs
Market	1.42	0.99	0.06	1	1.08	1.28
Dynamic	3.99	3.4	2.1	2.12	3.92	2.23
Innovation	5.66	5.18	4.51	3.25	2.52	2.78
Resource	3.09	4.04	3.68	1.59	2.1	4.35
Industry	4.1	4.86	2.49	1.02	4.49	4.28
Political	3.92	3.79	6.75	4.7	5.55	3.05

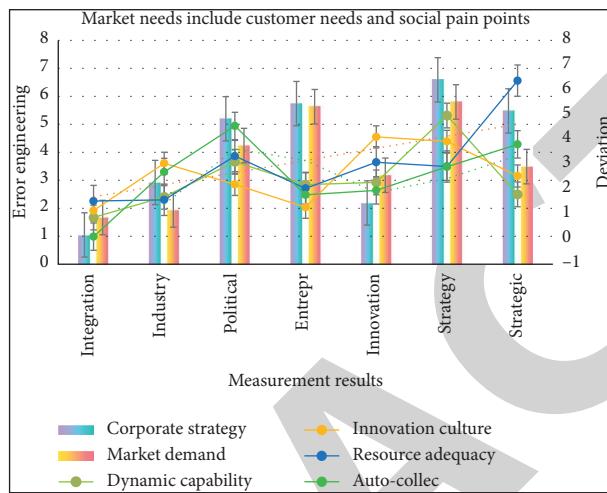


FIGURE 3: Market needs include customer needs and social pain points.

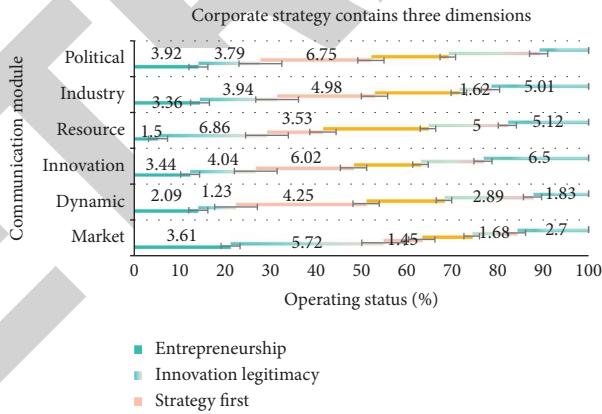


FIGURE 4: Corporate strategy contains three dimensions.

TABLE 3: Take innovation atmosphere as an example to illustrate the impact on platform innovation.

Item	Corporate strategy	Market demand	Dynamic capability	Innovation culture	Resource adequacy	Autocollect
Integration	1.05	1.67	0.88	1.16	1.54	0.11
Industry	2.92	1.94	1.71	3.06	1.59	2.71
Political	5.2	4.24	3.12	2.21	3.35	4.56
Entrepreneurship	5.74	5.63	2.2	1.29	2.05	1.79
Innovation	2.19	3.18	2.29	4.12	3.1	1.97
Strategy	6.59	5.8	4.98	3.94	2.93	2.92
Strategic	5.48	3.49	1.81	2.55	6.38	3.82

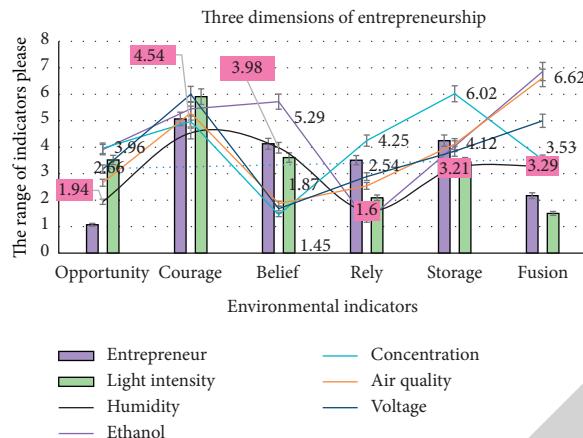


FIGURE 5: Three dimensions of entrepreneurship.

TABLE 4: Matlab assumes the simulation conditions.

Item	Entrepreneur	Humidity	Light intensity	Ethanol	Concentration	Air quality	Voltage
Opportunity	1.07	1.94	3.52	3.91	3.96	2.66	3.17
Courage	5.07	4.54	5.91	5.45	4.97	5.29	6
Belief	4.13	3.98	3.61	5.72	1.45	1.87	1.68
Rely	3.51	1.6	2.09	1.23	4.25	2.54	2.89
Storage	4.25	3.21	3.44	4.04	6.02	4.12	3.85
Fusion	2.17	3.29	1.5	6.86	3.53	6.62	5

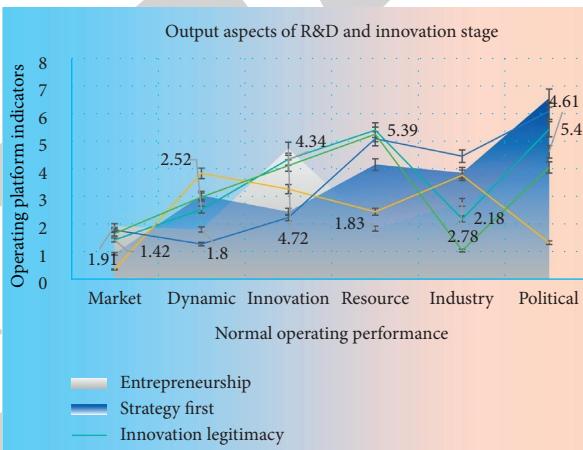


FIGURE 6: Output aspects of R&amp;D and innovation stage.

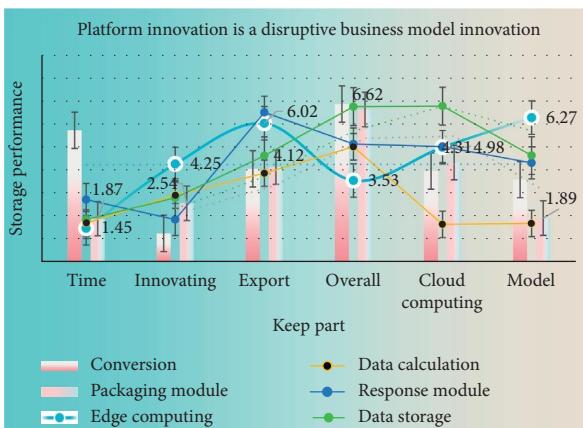


FIGURE 7: Platform innovation is a disruptive business model innovation.

TABLE 5: Revise the concept category obtained from data analysis.

Item	Conversion	Edge computing	Packaging module	Data calculation	Response module	Data storage
Time	5.72	1.45	1.87	1.68	2.7	1.83
Innovating	1.23	4.25	2.54	2.89	1.83	2.78
Export	4.04	6.02	4.12	3.85	6.5	4.61
Overall	6.86	3.53	6.62	5	5.12	6.75
Cloud	3.94	4.98	4.31	1.62	5.01	6.77
Model	3.57	6.27	1.89	1.66	4.3	4.62

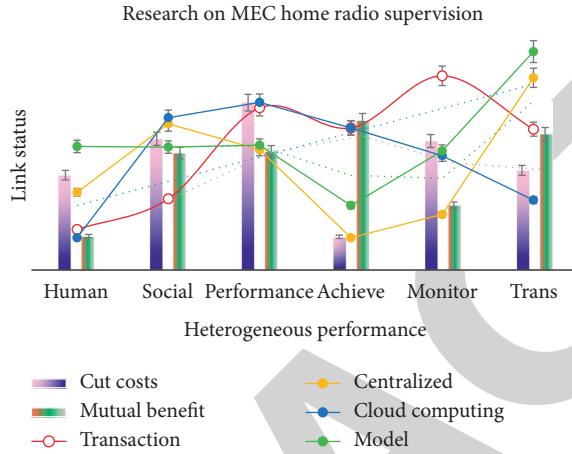


FIGURE 8: Motivation of enterprise platform innovation and innovation resources.

TABLE 6: Social network relationships formed by the interaction between external organizations.

Item	Transaction	Cut costs	Mutual benefit	Centralized	Cloud computing	Model
Human capital	4.89	3.35	2.02	1.06	1.12	1.72
Social network	3.34	3.26	6.32	2.48	3.18	4.58
Performance	3.14	4.81	4.22	1.28	6.21	3.13
Achieve	6.13	5.11	2.96	5.7	5.52	5.4
Monitor	4.75	4.34	3.24	4.54	2.42	1.52
Trans	2.74	2.12	2.9	3.47	4.69	3.54

by the interaction between enterprises and external organizations such as upstream and downstream suppliers and customers is conducive to the acquisition of knowledge and resources, thereby promoting platform innovation. For example, CCB has 6 million corporate client resources and integrates these resources together to build a matching platform, allowing customers to generate transactions, reduce costs, and benefit each other through the platform, and finally stick these customers through the platform.

As shown in Figure 9, although the main case collects a large amount of primary and secondary data, the secondary case uses only secondary data as analysis data, which has certain reliability and validity limitations and may have a certain impact on the final model. This article selects only a small number of research cases and the number of samples collected is limited. The selected cases are all well-known domestic companies, and they are companies with successful platform innovations. They lack universality. If more on-site interviews and surveys

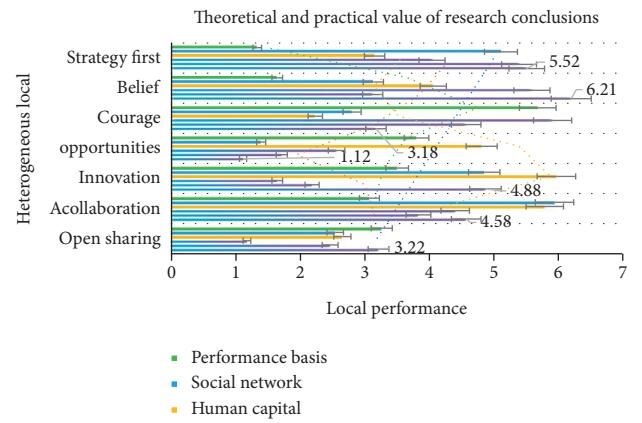


FIGURE 9: Theoretical and practical value of research conclusions.

can be used, a number of small and medium-sized interviews on companies' platform innovations will enhance the theoretical and practical value of research conclusions.

## 5. Conclusions

The cities with double high manufacturing industries are coastal cities and provincial capital cities. The two-stage efficiency of manufacturing in these cities is higher than the national average. The reason may be that, on the one hand, these cities have a better educational foundation and more R&D resources, which can attract more high-tech enterprises to settle in and acquire more R&D and innovation resources, which will help them improve the efficiency of R&D and innovation. On the other hand, these cities are located in coastal areas. The proportion of export industries in the manufacturing industry is relatively high, and they have a good industrial foundation. They have formed a relatively complete industrial infrastructure and related industrial supporting facilities. The market economy is relatively more active. Export transformation of scientific and technological achievements of manufacturing companies provides a good environment and foundation. Cities that are twice as low in manufacturing are in the Midwest or Northeast. The cities where these manufacturing industries are located are relatively weak in R&D and innovation. It is difficult to provide strong R&D resources for manufacturing R&D and innovation activities, and it is difficult to attract them. Enough R&D talents carry out the corresponding R&D and innovation activities, resulting in relatively low R&D and innovation efficiency.

At the same time, these manufacturing cities have weak economic foundations, insufficient market economy development, a relatively low proportion of export industries, and inadequate industrial infrastructure facilities, poor innovation awareness and atmosphere, and a low degree of openness. It is not conducive to the export transformation of R&D achievements, resulting in low efficiency in the export transformation of scientific and technological achievements of manufacturing industries in these cities. From the regression results, the urban economic development level and manufacturing human capital have a significant positive impact on the efficiency of manufacturing R&D innovation, indicating that a high level of urban economic development can provide a good economic foundation for manufacturing R&D innovation. The improvement of human capital can provide a large number of R&D and innovative talents for manufacturing R&D and innovation and promote the improvement of manufacturing R&D and innovation efficiency. The city's technological level has a positive impact on the efficiency of manufacturing R&D innovation, but it is not significant. The reason may be that there is an obvious "fence" between the city's investment in technological innovation and the R&D and innovation activities of the manufacturing industry. Although the city's investment in technological innovation can promote local technological innovation activities, it interacts with the manufacturing industry. Insufficiently, it has not been able to significantly promote the improvement of manufacturing R&D and innovation efficiency.

From the perspective of export conversion efficiency, the degree of urban openness, debt financing, and the efficiency of R&D innovation have had a significant positive impact on

it. The reason may be that the increase in the degree of urban openness can promote the exchange and cooperation between the manufacturing industry and foreign countries and improve the efficiency of export conversion. At the same time, the export of high-tech products often has higher production quality and requirements and requires more investment. Therefore, the manufacturing industry can improve the export conversion efficiency of products through debt financing. From an innovation-driven perspective, R&D innovation efficiency has a significant positive impact on export conversion efficiency. The manufacturing industry continues to improve the technological content of export products through the development of R&D and innovation activities. While improving the efficiency of R&D and innovation, it can significantly promote the improvement of export transformation efficiency. This also further shows that by continuously improving the quality and efficiency of R&D and innovation, the high-quality development of manufacturing export trade will continue to be promoted, and it also confirms the inference that R&D and innovation efficiency will have a significant positive impact on export conversion efficiency. Geographical distance has a significant negative impact on export conversion efficiency, indicating that cities closer to the coastline, especially coastal cities, have higher export conversion efficiency. From the perspective of the influencing factors of overall efficiency, the level of urban economic development and debt financing has had a significant positive impact on it.

## Data Availability

The data underlying the results presented in the study are available within the manuscript.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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