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Original scientific paper

Research on Optimal Allocation of High-Quality Development of Digital Manufacturing Based on a Priori Improved Algorithm

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Abstract: In response to the challenges faced by the development of the manufacturing industry, this paper will theoretically examine the influence mechanism of digital investment on the quality improvement of the manufacturing industry, and based on the distribution structure of factors, study the transmission mechanism of digital investment on the quality development of the manufacturing industry. Considering the attributes of digital manufacturing, including a large volume of customer business and complex data, and combined with the reality of the manufacturing industry, an enhanced APRIORI algorithm, called the PAP algorithm, is proposed. This algorithm generates frequent item sets by establishing the minimum support and confidence levels, calculates the association strength of manufacturing services, and determines the optimal execution path of combined services. The level of digital input is evaluated through three dimensions: digital infrastructure, application level and technological innovation. The high-quality development level of the manufacturing industry was evaluated from four dimensions: economic benefits, green development, innovation-driven development and social benefits, and the regional development status of digital input and high-quality development of the manufacturing industry was further analyzed.

Keywords: compose service execution paths; digitization; improved a priori algorithm; manufacturing; optimize the configuration

1 INTRODUCTION

In the context of the in-depth development of the digital economy, digital investment has become the core engine to rebuild the manufacturing factor distribution system and promote the high-quality development of the industry. As a new production factor, data can accurately identify market needs and optimize production processes through full link acquisition, analysis and intelligent decision-making. For example, the circulation industry data system, built with multi-point digital intelligence, transforms industry experience into a standardized tool to achieve a leap in supply chain efficiency. Technology integration results in a change in the structure of factor allocation. This intelligent transformation of factor allocation not only promotes manufacturing enterprises, but can also be developed into advanced models, such as predictive maintenance and flexible production, but also improves total factor productivity through industrial ecology, building a "data-driven technology-enabled efficiency transformation" innovation loop for high-quality economic development. Its strategic value for breaking through resource constraints and cultivating new quality productivity has been fully verified in practice, and it also effectively promotes the development of industrial digitization and digital industrialization, which is an important driving force for the high-quality development of the manufacturing industry [2].

Driven by personalized and diversified market needs, manufacturing tasks are becoming more and more complex. The rapid increase in the number of manufacturing services has led to an exponential increase in the number of manufacturing services portfolio, and it has become a hot issue to better combine manufacturing services or select matching manufacturing services. Limited by problems such as insufficient capacity, a single or simple manufacturing service cannot solve the complex collaborative manufacturing tasks in intelligent manufacturing. The existing manufacturing service composition methods mainly focus on the research of adjacency related service composition, without considering the global structure characteristics of multi-order composite service composition, and cannot effectively solve the complex collaborative manufacturing tasks in manufacturing.

This research paper on digital input, factor allocation structure, and the high-quality development of the manufacturing industry aims to enhance the theoretical framework and expand the foundational theories of high-quality economic development. Additionally, it seeks to facilitate the transformation and upgrading of the manufacturing sector through factor allocation structure and to establish new avenues for research on the high-quality development of the manufacturing industry. Grasping developmental opportunities and overcoming developmental bottlenecks holds substantial theoretical significance for the manufacturing business. In addition, existing studies have explored the internal mechanism of manufacturing enterprises driving open innovation through digital capabilities, and pointed out that enabling open innovation through digital capabilities is an important way for manufacturing enterprises to gain competitive advantages in the digital economy [3]. Digitalization promotes cooperation between enterprises and a wider range of technology enterprises in the innovation process (i.e. the breadth of technology cooperation), and the implementation of digital transformation will have a positive impact on open innovation [4]. Open innovation is an innovation model that can absorb external resources to make up for internal shortcomings. It is of great significance to the digital transformation of manufacturing enterprises in response to environmental changes, innovating business models, improving innovation efficiency, and establishing cooperation ecosystems, and can promote digital transformation and upgrading. Based on the perspective of open innovation, in-depth analysis is made on the dynamic process of digital transformation of manufacturing enterprises. Explore the internal influence mechanism of open innovation on digital transformation and the process of digital transformation development of manufacturing enterprises under the open innovation mode, and build a path model of digital transformation of manufacturing enterprises.

2 RELATED WORK

From the viewpoint of superior economic development, the notion of high-quality manufacturing industry development is introduced, delineating the trajectory for the future of the manufacturing sector in the next developmental phase. In accordance with the context of economic development, we initiated the enhancement of high-quality manufacturing growth. Currently, no cohesive theoretical framework is endorsed by the majority of academics. Two indicators are employed to assess the growth quality of the manufacturing industry [5]. Research suggests that the principal objective for enhancing the quality of genuine economic development is to further intensify the supply-side structural reform of the manufacturing sector. The industrial development quality measurement model employs normal cloud and correlation function approaches to assess measurements across three distinct dimensions: horizontal cross section, temporal variation, and future trend [7]. To mitigate the constraints associated with a singular indicator for assessing the development and growth of the industrial manufacturing sector, an increasing number of scholars are evaluating and analyzing various indicators of high-quality and rapid growth from diverse perspectives and dimensions, including economic benefits, production efficiency, product quality, industrial structural adjustment, and international market competitiveness.

The high-quality development of the manufacturing industry is completely assessed based on five fundamental aspects: technological innovation, coordinated development, green ecology, openness to the external environment, and resource sharing. The primary reasons propelling the high-quality development of the manufacturing industry include scientific and technological advancement, market competitiveness, industrial enhancement, and foreign direct investment. The study revealed that the extent of government support resulted in both the promotion and inhibition of the development quality of manufacturing companies due to government subsidies, leading to an overall performance characterized by a "masking effect" [10]. The correlation between the agglomeration of producer services and the development of the manufacturing industry is characterized by a U-shaped curve. Empirical study suggests that producer services can substantially enhance the developmental quality of the manufacturing industry by augmenting technological innovation capabilities and optimizing industrial structure allocation [11]. A theoretical framework for the high-quality development of the manufacturing industry is proposed, grounded in the principles of innovation, economy, ecology, openness, and advancement. It is asserted that the level of high-quality development in this sector exhibits a significant positive correlation with spatial development and demonstrates a notable spatial distribution trend [12]. Emphasizing the five development principles, it is suggested that many measures be concurrently advanced to facilitate the high-quality development of manufacturing [13]. The high-quality development of the manufacturing industry should be further assessed and studied in terms of innovation and openness, social equity, quality brand establishment, and governmental support, with particular emphasis on social equity.

Relevant scholars have undertaken empirical investigations regarding digital input and the high-quality advancement of the manufacturing sector, primarily concentrating on three key variables. The initial consideration is the effect on manufacturing export firms. A significant number of researches have examined the factors influencing the export added value of firms [15]. According to the Melitz model, the Internetization of firms is enhanced, suggesting that as the level of Internetization increases, enterprises will utilize domestic intermediate inputs more. Through the design of a theoretical model examining the impact of the digital economy on export commerce via a multi-channel mechanism [16], the digital economy exerts a multi-faceted reconstructive effect on the international competitiveness of the manufacturing sector: initially, leveraging cross-border data flow and technological collaboration networks, digital technology generates substantial geographical spillover effects through interregional knowledge diffusion and the reorganization of production factors. Its marginal benefits exhibit a nonlinear pattern characterized by initial acceleration followed by convergence, thereby facilitating the self-reinforcing trajectory of the manufacturing industry's globalization. Subsequently, drawing on the dynamic comparative advantage theoretical model, the integration of digital factors transforms the conventional factor endowment structure, advancing the manufacturing sector along the continuum of "process upgrading product upgrading function upgrading" by establishing a data-driven global resource allocation mechanism and a technology integration platform. This dual effect creates a new impetus for the manufacturing sector to transcend the "low-end lock" in the digital age, and its theoretical framework provides a more robust explanatory power regarding the interaction between factor coupling degree and upgrade threshold. Examine the internal dynamics of "Internet+" to augment the value chain of the manufacturing sector. This paper adopts the panel data from 2005 to 2015 and uses the spatial Durbin model to investigate the impact of "Internet Plus" on the improvement of the manufacturing value chain. It is believed that "Internet Plus" promotes the improvement of the manufacturing value chain and stimulates the growth of manufacturing in adjacent regions. By integrating intelligence and global value chain (GVC) division of labor within a unified analytical framework, both theoretical and empirical studies systematically validate the impact of intelligent transformation on GVC positioning. They elucidate the mechanisms through which regional division levels are enhanced via technology diffusion and organizational innovation, and affirm that advancements in intelligence can transcend factor limitations, thereby establishing new competitive advantages in the global arena. A digital input measurement system is developed based on the production correlation strength index within the context of industrial collaboration. The direct consumption coefficient of the communication equipment manufacturing sector is termed hardware penetration, while the consumption coefficient of the information service sector signifies software integration [19]. Quantitative research indicates that the input intensity of both dimensions increases by one standard deviation each time. The growth rates of primary business income in the manufacturing sector rose by 2.3% and 3.1%, respectively. This dual digital penetration mode establishes a collaborative upgrade trajectory of "hardware foundation-software value-added" by reconfiguring production functions and value creation methodologies, offering a systematic solution for the comprehensive transition of the manufacturing sector. Its operational mechanism demonstrates accelerated enhancement when the digital maturity of the industrial chain surpasses a certain threshold. Analyze the disparity in digital input levels regarding their economic impact on manufacturing subsectors. Conversely, regarding the regional development of the manufacturing industry, empirical research indicates that enhancing regional digital access will positively influence innovation performance. Furthermore, the effects of digital equipment, platform construction, and application level on innovation performance exhibit an inverted U-shaped relationship. The digital economy in the east, west, and south exerts a more substantial influence on the industrial industry [21]. The evolution from "information technology" and "Internet +" to the extent of digital investment in the digital economy has consistently been a focal point of research both domestically and internationally. The pertinent research on the high-quality advancement of the manufacturing sector is grounded in the framework of high-quality economic development, informed by the new development paradigm, and delineates the developmental trajectory of the manufacturing industry in this new phase. This research examines, theoretically, the effect of digital input on high-quality economic development, while empirically analyzing the impact on export trade enterprises, the enhancement of the global value chain, and the developmental trajectory.

This work further investigates the modification of the number of factors contributing to urban road traffic accidents, based on the enhanced Apriori algorithm. Based on the level and dimension of specific qualities, parameters such as support, confidence, and lift are employed to identify robust association rules among causal components, and the outcomes are subsequently refined to extract significant association rules [22, 23]. A deep convolutional neural network and a random forest algorithm are employed to forecast accident risk [24]. The former employs random forests with several decision trees to generate the probability of traffic accidents and utilizes geographical detection techniques to examine various parameters influencing accident casualties. This paper presents an algorithm for mining multi-valued attributes. This concept primarily involves transforming the association rules of multi-valued characteristics into Boolean association rules [25, 26], followed by employing the Apriori algorithm for mining computations. This method possesses certain limitations that will lead to a constant growth in the attribute value of the transaction database, resulting in data complexity and significant challenges for the mining process. In recent years, numerous endeavors have been made regarding multi-valued attribute algorithms, which partially address the issue of association rule transformation. However, the matrix in data storage and processing also introduces additional challenges, complicating the calculations significantly. Numerous endeavors exist to employ association rules to enhance data mining algorithms [27, 28], nonetheless the correlation of identical attribute values remains unavoidable in this method. The intricate attribute value of data influences algorithm efficiency; conversely, the algorithm's application does not engage with the processing of identical attribute value connections, so impacting mining efficiency.

3 COMBINATORIAL OPTIMIZATION METHOD FOR HIGH QUALITY DEVELOPMENT OF MANUFACTURING BASED ON APRIOR IMPROVED ALGORITHM

3.1 Optimization of Manufacturing Service Combination Based on Apriori Algorithm

By summarizing and sorting out the theoretical mechanism of the impact of digital input on the high-quality development of manufacturing industry, and based on the perspective of factor allocation structure, the transmission mechanism of digital input on the high-quality development of manufacturing industry is deeply studied. Second, due to the rapid development of the level of digital investment, there is a large "digital divide" between different regions. Therefore, the research object is focused on the overall development of the manufacturing industry in and its various regions, and the heterogeneity research is carried out in different regions. The technical research diagram is shown in Fig. 1.

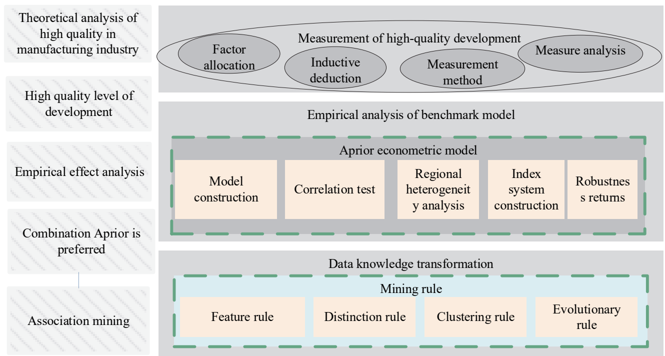

Figure 1 Technology research roadmap

In the face of massive data, how to establish an effective conversion between data and knowledge and get valuable information has become an urgent problem to be solved. Under this background, data mining comes into being. The rules excavated from the database are as follows: feature rules, distinction rules, clustering rules, association rules and evolution rules.

3.2 Improved Apriori Algorithm is Preferred in Combination

A technique and system for optimizing the combination of manufacturing services based on the Apriori algorithm are proposed. The system consists of a screening module for frequent-item manufacturing services, which first sets the minimum support and confidence thresholds of the Apriori algorithm, and then uses the algorithm to traverse the database and extract frequent item sets. It also includes a module for calculating the correlation strength of manufacturing services, which analyzes frequent item sets to determine the correlation strength. The selection module generates the combined service execution path and evaluates the average value of adjacency correlation in each path to identify the optimal combined service execution path. The invention identifies the most effective combination of manufacturing services based on the strength of their correlations and establishes the optimal execution pathway for this service combination. The frame diagram is illustrated in Fig. 2.

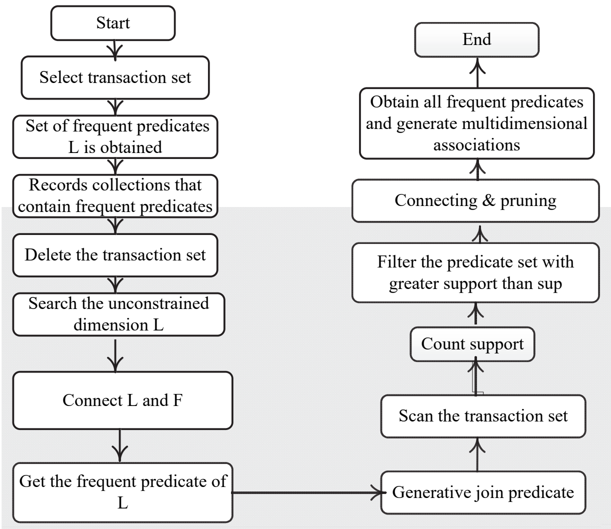

Figure 2 Block diagram of improved combinatorial Apriori algorithm

1. As shown in Fig. 2, there are the following steps:
(1) Frequent screening of manufacturing services, including:
① Firstly, the minimum support degree min-sup and minimum confidence degree min-conf of Apriori algorithm are determined.
② Apriori algorithm is used to traverse the manufacturing service database to determine whether the support degree of candidate services is greater than or equal to the minimum support degree;
③ Generate a frequent item manufacturing service set with frequent item manufacturing service greater than or equal to the minimum support;

Step (2) Calculation of the correlation strength of manufacturing services, including:
① The frequent item manufacturing service set is traversed, and the confidence of the service combination is used to determine whether there is the interdependency of the sequential service;
② The correlation strength of the manufacturing service combination meeting the conditions is calculated, and then the manufacturing service combination with the maximum correlation strength is determined, and the combined service execution path is generated from the manufacturing service combination with the maximum correlation strength;

Step (3) Selection of optimal manufacturing service portfolio execution path, including:
① Compare the average correlation strength of the adjacency correlation in each composite service execution path;
② Select the composite service with the highest average association strength, so as to obtain the best composite service execution path.

2. According to the optimization method of manufacturing service combination based on Apriori algorithm.

RS_i and RS_j represent manufacturing services, i and j are the serial numbers of manufacturing services, x is the number of occurrences of the manufacturing service RS_i in the execution path set of the manufacturing service composition, and n is the quantity of all manufacturing services. Then, the support level of the manufacturing service RS_i is defined as:

$$s(i) = x/n \tag{1}$$

Confidence represents the probability that manufacturing service RS_j and manufacturing service RS_i appear in the service composition execution path as sequential services, expressed by the following equation:

$$C(RS_i \leftrightarrow RS_j) = \frac{< RS_i, RS_j >}{| RS_i || RS_j |} \tag{2}$$

3. According to the Apriorialgorithm based manufacturing service portfolio optimization method:

According to the calculation formula of manufacturing service support, calculate the support degree of each manufacturing service in the manufacturing service database, and judge whether its support degree is greater than or equal to the minimum support degree, that is, judge $s(i)$ >= min-sup.

4. Step 2 specifically includes: strong correlation, moderately strong correlation, moderately weak correlation according to the definition, if the correlation is as follows:

Strong correlation:

$$C(RS_i \leftrightarrow RS_j) \geq \min - conf \tag{3}$$

Moderately strong correlation:

$$\min - conf \geq C(RS_i \leftrightarrow RS_j) \geq 0.8 * \min - conf \tag{4}$$

Moderately weak correlation:

$$0.8 \times \min - conf \geq C(RS_i \leftrightarrow RS_j) \geq 0.6 \times \min - conf \tag{5}$$

Weakly correlated:

$$0.6 \times \min - conf \geq C(RS_i \leftrightarrow RS_j) \geq 0.2 \times \min - conf \tag{6}$$

5. According to the Apriorialgorithm based manufacturing service portfolio optimization method:
$Rel(i, j)$ is the combinable relationship between RSi and RS_j. $S(i, j)$ is used to represent the support degree of manufacturing service RS_i and RS_j, and the correlation strength of manufacturing service RS_i and RS_j is obtained as follows:

$$r_s(RS_i, RS_j) = \sqrt{r_s(RS_i \to RS_j) r_s(RS_i \leftarrow RS_j)} \tag{7}$$

6. According to the Apriorialgorithm based manufacturing service portfolio optimization method: The average correlation strength of the execution paths of the manufacturing services portfolio corresponding to the four correlations is calculated

$$\bar{X} = \frac{\sum_{N} \sqrt{r_s(RS_i \to RS_j) r_s(RS_i \leftarrow RS_j)}}{N} \tag{8}$$

N represents the number of manufacturing services in the manufacturing service composition execution path corresponding to each of the four dependencies.

7. A manufacturing service portfolio optimization system based on Apriori algorithm is characterized by:
(1) A filtering module for frequently manufactured services.

① Determine the min support and min confidence MinConf of Apriori algorithm;

The Apriori algorithm is used to traverse the manufacturing service database to determine whether the degree of support for candidate services is greater than or equal to the minimum degree of support;

(3) Generate a frequent item manufacturing service set with frequent item manufacturing service greater than or equal to the minimum support;

(2) Correlation strength calculation module for manufacturing services for:
(1) The frequent item manufacturing service set is traversed, and the confidence of the service combination is used to determine whether there is the interdependency of the sequential service;
(2) The correlation strength of the manufacturing service combination meeting the conditions is calculated, and then the manufacturing service combination with the maximum correlation strength is determined, and the combined service execution path is generated from the manufacturing service combination with the maximum correlation strength;
(3) A selection module for the optimal manufacturing service portfolio execution path for:
(1) Compare the average correlation strength of the adjacency correlation in each composite service execution path;
(2) Select the composite service with the highest average association strength, so as to obtain the best composite service execution path.

3.3 Measurement of High Quality Development Level of Manufacturing Industry

Develop an assessment framework for the high-quality advancement of the manufacturing sector. The index system comprises three tiers: the first tier is the target level, representing the overall high-quality development of the manufacturing sector in each region; the second tier is the business layer, which formulates an indicator system based on economic benefits, green development, innovation-driven initiatives, and social benefits. The third layer is the indicator layer, comprising data from ten indications. Refer to Tab. 1 for specifics.

Table 1 Measurement index construction of high-quality development of manufacturing industry

Target layer	Business layer	Index level	Index interpretation	Indicator direction
High-quality development of manufacturing industry	Economic benefit	Contribution rate of industrial output	Gross regional product	Forward direction
		Labor productivity	Manufacturing employment at the end of the year	Forward direction
		Industrial profit rate	Gross manufacturing profits	Forward direction
		Wastewater discharge intensity	Manufacturing output value	negative
	Green development	Industrial solid waste emission intensity	Manufacturing output value	negative
		Utilization rate of solid waste	Amount of solid waste produced	Forward direction
		Energy consumption intensity	Output value consumed by manufacturing	negative
	innovation-driven	Technological innovation input level	Internal expenditure of manufacturing funds	Forward direction
		Technological innovation output level	Manufacturing invention patent	Forward direction
	Social benefit	Employment level	Manufacturing employment	Forward direction
		Wage level	Manufacturing wages	Forward direction

The research adopts the range standardization method to carry out dimensionless processing on the data in the index layer (the measurement indicators in the high-quality development of manufacturing industry include positive indicators and negative indicators) respectively:

$$\begin{cases} d_{ij} = \dfrac{x_{ij} - x_{ij\min}}{x_{ij\max} - x_{ij}} (Forward) \\ d_{ij} = \dfrac{x_{ij\max} - x_{ij}}{x_{ij\max} - x_{ij\min}} (Negative) \end{cases} \tag{9}$$

Calculate the proportion of the *i* province (city, district) in item j index as follows:

$$P_{a_{ij}} = \frac{Z_{a_{ij}}}{\sum_{a} \sum_{i} Z_{a_{ij}}} \tag{10}$$

Calculate the entropy value:

$$E_j = -K_1 \sum_{k} \sum_{i} P_{a_{ij}} LN(P_{a_{ij}}) \tag{11}$$

Calculate the redundancy of data of each indicator layer:

$$D_j = 1 - E_j \tag{12}$$

Calculate the weight:

$$W_j = \frac{D_j}{\sum_i D_j} \tag{13}$$

Calculate the overall score of manufacturing quality development W in each region P:

$$I_{a_{ij}} = P_{a_{ij}} * W_j \tag{14}$$

Manufacturing enterprises digital transformation, with the help of digital technology, manufacturing enterprises will transform the traditional manufacturing industry to improve the process, and then achieve cost reduction, quality improvement, innovation, efficiency. On the one hand, digital transformation can digitally transform production factors such as equipment, process and raw materials to make them have corresponding intelligent attributes, such as the precise design and production of equipment and raw materials through digital twin technology. On the other hand, in the process of digital transformation, data becomes a key element, and data analysis provides support for business decisions. With the application of digital technology, the development of manufacturing enterprises has encountered new opportunities, and there is also a strong support for promoting digital transformation.

Digital transformation to enhance the level of manufacturing technology and capabilities. Specifically, first, with the help of digital transformation, manufacturing technology can promote the intellectualization of the whole process from design, research and development to production, research and development costs and research and development cycles can be reduced, and research and development efficiency can be improved. Secondly, through digital transformation, manufacturing technology can achieve real-time monitoring and management of the production process, and utilize artificial intelligence technology to realize intelligent control of the production process and reduce production costs. Thirdly, through digital transformation, manufacturing technology can achieve the integration, informatization and visualization of management processes, thereby enhancing management efficiency. Therefore, digital technology can be integrated with manufacturing technology to form an intelligent manufacturing system, which can reduce manufacturing costs while improving the research and development efficiency, production efficiency and management efficiency of manufacturing enterprises. Specifically, through digital transformation and upgrading of key equipment and parts manufacturing capabilities such as CNC machine tools, digital technology can provide new tools, new methods and new ideas for the design of key equipment and parts such as CNC machine tools.

3.4 Research on Regional Difference of High Quality Development in Manufacturing Based on Apriori Improved Algorithm

In order to further reveal the regional disparity of high-quality development level of manufacturing industry, this paper uses Gini coefficient to measure the difference of high-quality development level of manufacturing industry.

The Gini coefficient is calculated as follows:

$$G = \frac{\sum_j \sum_h \sum_r | y_{ji} - y_{hr} |}{2n^2 \bar{y}} \tag{15}$$

Let G represent the overall Gini coefficient, y denote the average high-quality development level of the manufacturing sector across provinces, n signify the number of provinces, K indicate the number of regions, and y_{ij} refer to the high-quality development level of the manufacturing industry in region i of table j(h).

Tab. 2 illustrates the overall and inter-regional inequalities in the high-quality development level of the manufacturing industry, as assessed by the Gini coefficient and its decomposition method. By further analyzing the high-quality development levels of the manufacturing industry based on the spatial scales of east, central, and west, the primary sources of the disparities in high-quality development levels may be elucidated.

Table 2 Gini coefficient and its decomposition of high-quality development index of manufacturing industry and various regions during 2014-2023

Gini coefficient		2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
G	Totality	0.3751	0.3559	0.3243	0.3064	0.292	0.279	0.285	0.281	0.2727	0.264
	East	0.2904	0.2842	0.2604	0.2602	0.2489	0.2345	0.2363	0.23 09	0.2248	0.2276
G_{ij}	Middle part	0.1631	0.1604	0.1566	0.1537	0.1528	0.1469	0.1443	0.132	0.13 83	0.1279
	west	0.2946	0.2445	0.2174	0.192	0.1676	0.1725	0.1854	0.1804	0.1766	0.166
	East-Central	0.3813	0.3771	0.364	0.359	0.3429	0.3188	0.3125	0.3132	0.3021	0.2972
G_{jh}	East-West	0.5373	0.5128	0.4646	0.4255	0.4046	0.3843	0.3974	0.3868	0.3763	0.3608
	Midland-west	0.2921	0.2454	0.2151	0.1828	0.1763	0.1837	0.2046	0.2049	0.2015	0.1859
Contribution rate	In the area	24.582	24.353	24.476	25.295	25.168	25.368	25.23 8	25.233	25.31	25.623 6
	interregional	68.66	70.022	69.634	67.482	66.82	65.623	65.718	64.453	63.866	62.389
	Supervariable density	6.7645	5.63	5.897	7．215	7.04	9.018	9.0314	10.334	10.828	11.98

Tab. 2 indicates that the overall regional disparity diminished steadily during the sample period, decreasing from 0.3751 in 2011 to 0.2640, with an average yearly reduction of 3.79%, so indicating a steady convergence of regional differences. From the viewpoint of regional disparities, the east and the west reflect the present state of high-quality development in the industrial sector.

The center and western regions had a declining tendency. The Gini coefficient reveals significant spatial disparities in the high-quality development of the manufacturing industry between provinces in the eastern and western regions, indicating a "polarization phenomenon" in the high-quality development levels of the manufacturing sector in the eastern region. The manufacturing industry's high-quality development level in eastern provinces like Beijing and Shanghai significantly surpasses that of Hainan, another eastern province. The manufacturing industry's high-quality development in Sichuan and Shaanxi significantly surpasses that of Gansu, Qinghai, Ningxia, and other provinces. The high-quality development of the manufacturing industry in the central region is largely uniform among provinces, with no significant polarization evident in the area. The disparity in the high-quality development levels of the manufacturing industry across various locations is progressively moving towards a balanced state.

The degree of contribution indicates that inter-regional disparities are the primary source of geographical variation in the high-quality growth of the manufacturing industry. Despite some fluctuations in the degree of contribution, the inter-regional difference accounts for over 60% of the overall difference, significantly surpassing the contribution rate of intra-regional difference and super-variable density. Intra-regional differences account for approximately 25% of the spatial differences in high-quality development of the manufacturing industry during the sample period, indicating that intra-regional differences are not the main factors affecting these spatial differences. The influence of hypervariable density on the spatial difference of high-quality manufacturing development is significantly smaller than that of intra-regional and inter-regional differences, remaining at around 10% throughout the sample period. Consequently, the overlap issue between distinct regions exerts negligible influence on the spatial disparity of high-quality manufacturing development.

5 SIMULATION VERIFICATION

This paper conducts an experimental comparison to verify the operational efficiency of the enhanced algorithm against the HBE-Apriori (Hashed Binary Encode-Apriori), FP-Growth(Frequent Pattern Growth), and Apriori algorithms as referenced in literature [12], analyzing their performance under varying support levels and transaction quantities. The dataset utilized in the experiment is the Market-Basket dataset, comprising 8500 transactions.

In Experiment 1, the total number of database transactions remains constant, but the execution time of the four methods is compared by varying the minimal transaction support threshold. The test outcomes are presented in Tab. 3.

Tab. 3 illustrates that, with a constant number of transactions and a steady increase in minimum transaction support, the execution time of the four algorithms consistently decreases, albeit at varying rates of reduction. The reduction in amplitude of the Apriori algorithm, FP-Growth algorithm, and HBE-Apriori algorithm is markedly more substantial than that of the enhanced method. To directly illustrate the comparison of the running times of the four algorithms, the visual representation of the experimental results in Tab. 3 is depicted in Fig. 3.

Table 3 Running time of the four algorithms with different transaction support levels

Minimum transaction support (%)	Apriori algorithm running time /s	HBE-Apriori algorithm Running time /s	FP-Growth algorithm runtime /s	Improved algorithm run time /s
10	68.57	30.16	39.61	17.74
16	48.67	24.35	27.74	8.54
20	38.89	15.75	20.17	6.17
25	27.76	9.37	14.73	3.96
30	21.03	5.23	7.28	2.43
35	14.91	3.14	4.78	1.53
40	12.68	2.18	2.37	0.95

Fig. 3 illustrates that when transaction support progressively increases, the execution time of the Apriori algorithm, FP-Growth algorithm, HBE-Apriori method, and the enhanced algorithm all exhibit a steady drop; however, the rate of fall for the enhanced algorithm is less pronounced than that of the other three algorithms. As the minimum transaction support thresholds are set at 35 and 40, the execution time of the enhanced algorithm diminishes gradually. The fall rate of the enhanced algorithm is nearly identical, since the progressive increase in transaction support results in a reduction of frequent item sets produced by the four algorithms. The frequency of database scans conducted by the Apriori algorithm diminishes as the quantity of generated candidate item sets declines, hence enhancing its operational efficiency. Nonetheless, when the frequency of item sets produced by the FP-Growth algorithm diminishes, the branches formed by the frequent pattern tree similarly decline. Furthermore, the algorithm requires merely two scans of the database, and its execution efficiency surpasses that of the Apriori algorithm.

HBE-Apriori algorithm and its enhanced variant. The execution efficiency improves as transaction support increases, given that the database is scanned just once. The enhanced method surpasses the HBE-Apriori algorithm due to its triple pre-pruning process. The enhanced approach has much greater efficiency compared to the traditional Apriori algorithm, FP-Growth algorithm, and HBE-Apriori algorithm, given a constant number of transactions and varying minimum support levels.

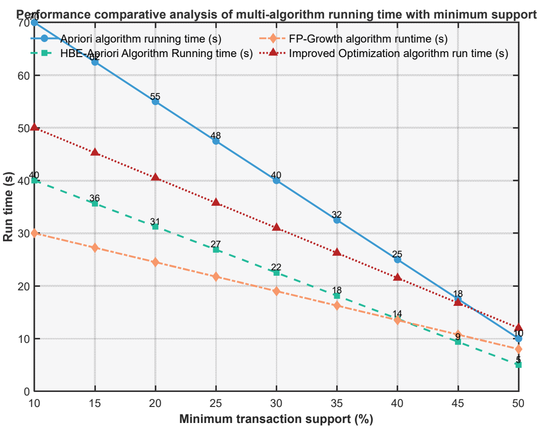

Figure 3 Comparison of runtime results of four algorithms with different minimum transaction support degrees

In Experiment 2, with the minimum support set at 30%, the execution time of the four algorithms is evaluated by varying the number of transactions. The test outcomes are presented in Tab. 4.

Table 4 Running time of four algorithms with different number of transactions

Transaction count	Apriori algorithm running time /s	HBE-Apriori algorithm Running time /s	FP-Growth algorithm runtime /s	Improved algorithm run time /s
1500	4.02	2.16	3.17	1.41
2500	7.68	3.65	5.46	1.72
3500	9.35	4.94	7.02	2.23
4500	11.98	6.73	9.74	2.82
5500	13.63	8.26	11.28	3.75
6500	17.29	9.37	15.91	4.15
8500	19.06	11.59	17.26	4.94

Tab. 4 illustrates that, with a constant minimum support degree, the execution time of all four algorithms escalates to differing extents as the number of transactions increases continuously. Nonetheless, the execution time of the Apriori, FP-Growth, and HBE-Apriori algorithms escalates considerably more rapidly than that of the enhanced approach. The operational efficiency of the enhanced method surpasses that of the conventional Apriori algorithm, FP-Growth algorithm, and HBE-Apriori algorithm.

To more effectively illustrate the comparison of the running times of the four algorithms, the visual representation of the experimental results in Tab. 4 is displayed in Fig. 4.

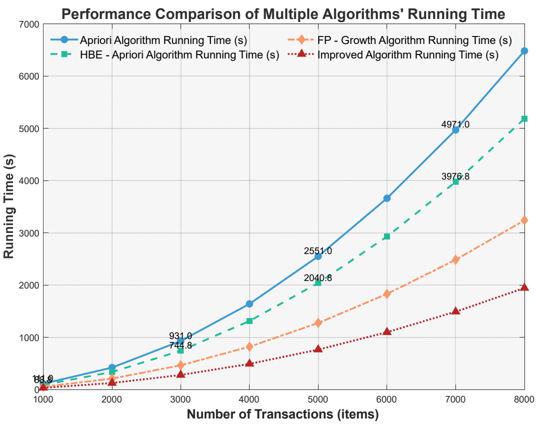

Figure 4 Comparison of runtime results of four algorithms with different transaction numbers

Fig. 4 intuitively demonstrates that when the number of transactions increases, the running time of the Apriori and FP-Growth algorithms escalates more significantly than that of the enhanced method and HBE-Apriori algorithm. As the volume of transactions progressively rises, the four algorithms will produce an increasing number of frequent item sets, and the algorithm's execution efficiency likewise improves with the augmentation of frequent item sets. The enhanced approach requires only a single database scan and three pre-prunings, resulting in superior execution efficiency compared to the previous three algorithms. The enhanced approach demonstrates superior efficiency compared to the traditional Apriori algorithm, FP-Growth algorithm, and HBE-Apriori algorithm when varying the number of transactions while maintaining a constant minimum support. Despite the enhanced operational efficiency of the upgraded algorithm relative to the other three algorithms, it still possesses certain deficiencies. If the database contains a substantial volume of data, the rows and columns of the top triangular matrix will be excessively lengthy, resulting in an increased time required to build the matrix.

In the general equipment manufacturing sector, the significance of input factors for ecological transformation reveals that the most critical inputs include #11 average wage of employed personnel, #25 proportion of output value from the high-tech industry, #26 proportion of output value from high-polluting industries, and #30 intensity of environmental regulations, among others. Fig. 5 below illustrates the partial dependence of industrial ecological transformation on these critical aspects. The *X*-axis denotes the dynamic variation of input factor scales, while the *Y*-axis illustrates the partial dependency effect of industrial ecological transformation on factor changes.

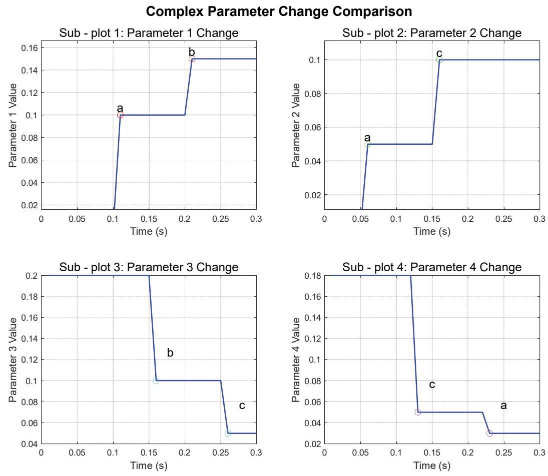

Figure 5 Partial dependence of key factors on ecological transformation of general equipment manufacturing industry

Fig. 5 illustrates that the partial dependence graph of these critical parameters for the ecological transformation of the industry resembles an *S*-shaped growth curve or an inverted *S*-shaped decline curve. In the *S*-shaped growth curves, exemplified by the average wage of employed persons for input factor #11 and the output value share of the high-tech industry #25 in Fig. 5, the growth rate remains relatively subdued prior to point an in the figure. At this juncture, the magnitude of the input component is rather minor relative to other factors, rendering the scale effect of the factor challenging to completely manifest. Subsequently, as the component size surpasses point a, the growth rate of the curve escalates swiftly, promptly attaining point *b*, the apex of the curve's slope. At this juncture, the scale effect of input variables is significant, and the marginal impact on the ecological transformation of the industry is increasing swiftly. At point *b*, the scale effect of input factors is completely manifested, the marginal effect is maximized, and the combination of input factors attains the optimal allocation equilibrium point. Ultimately, as the magnitude of input factors escalates, the curve's growth rate progressively diminishes. Upon surpassing point *c* in the diagram, the curve's growth rate becomes exceedingly gradual and approaches zero. In the phase subsequent to surpassing the *c* point, it indicates that the input factors are excessive relative to other factors, causing the combination of components to diverge from the optimal allocation equilibrium point, resulting in a quick decline in marginal benefit. In conclusion, when the scale of other input factors remains constant, the point exhibiting the highest growth rate on the partial dependence curve (proximal to point b in the picture) represents the optimal allocation equilibrium of the relevant input components. Simultaneously, it is observed that within the interval near point b [a, c], the partial dependence graph exhibits a significant growth rate, indicating that the dynamic variation of input factors yields substantial marginal benefits for ecological transformation; conversely, outside the interval [a, c], the growth rate of the partial dependence graph is minimal, and the augmentation of input factors provides only marginal benefits. Consequently, the interval [a, c] emerges as the ideal equilibrium range for the distribution of the two relevant input components.

Overall, according to the enhanced Apriori algorithm, the resilience level of the manufacturing industry chain exhibited a fluctuating upward trajectory from 2014 to 2023, with the metrics for resistance, resilience, and transformation generally reflecting an upward trend; notably, the scores for transformation were higher while those for resilience were lower. The trend chart clearly illustrates the resilience of the manufacturing industry chain and the variations across different dimensions, as depicted in Fig. 6 and Fig. 7.

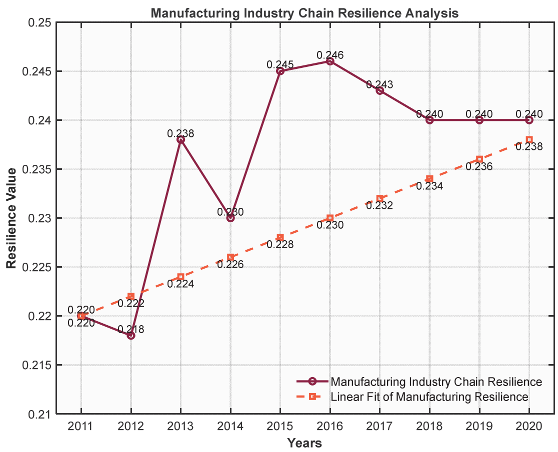

Figure 6 Change trend chart of measurement results of manufacturing industry chain resilience from 2014 to 2023

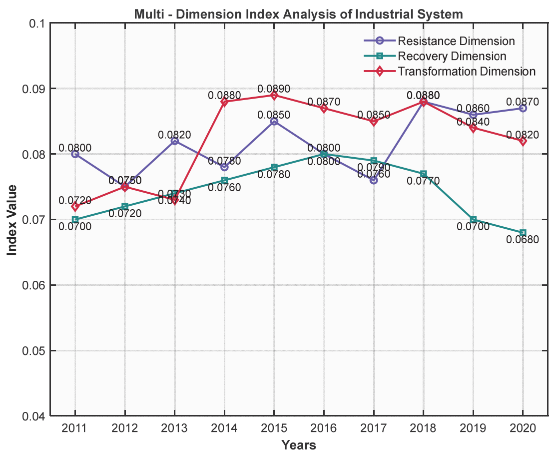

Figure 7 Change trend of measurement results of various dimensions of manufacturing industry chain resilience from 2014 to 2023

This chapter conducts simulation studies to assess the extent of improvement in the execution efficiency of the Apriori algorithm based on combinational logical bit operations. The execution efficiency of the traditional Apriori algorithm and the enhanced Apriori algorithm utilizing combinational logical bits is assessed and evaluated, with findings compared and analyzed. Fig. 8 illustrates the contrast of the algorithm's execution time.

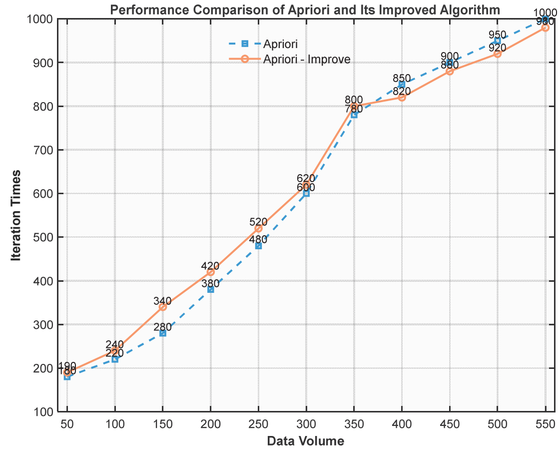

Figure 8 Comparison of execution time before and after the improvement of classic Apriori algorithm based on combinational logical bits

Assuming that the constraint is also set as the dimension of "defect type", under different support threshold conditions, frequent 1 predicate set is not considered (frequent 1 predicate set is not used to generate multidimensional association rules), and the comparison of the number of frequent predicate sets searched by the two algorithms is shown in Fig. 9.

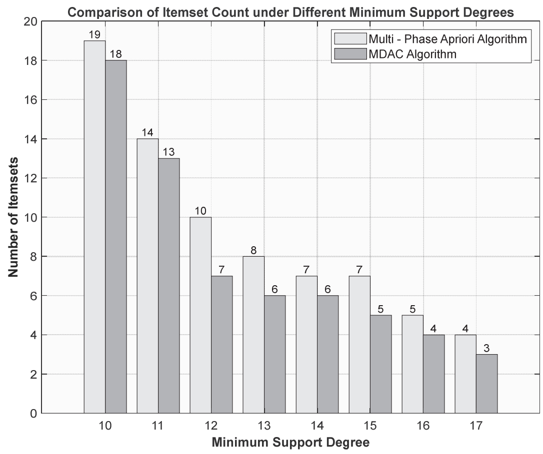

Figure 9 Comparison diagram of the number of frequent predicate sets generated under different support levels

As shown in Fig. 9, under different support thresholds, the number of frequent predicate sets searched by the improved Apriori algorithm based on constraints generally decreases, with a reduction of about 41.06%, compared with the multi-dimensional Apriori algorithm without constraints.

6 CONCLUSION

The empirical research results of the enhanced Apriori benchmark model in this paper show that the level of digital investment has a significant positive impact on the high-quality development of the manufacturing industry. Digital investment has extremely strong permeability and synergy, which is conducive to optimizing the allocation of factors and further promoting the high-quality development of the manufacturing industry. The results of the mediating effect model show that digital investment based on the factor allocation structure has a significant positive impact on the high-quality development of the manufacturing industry. Furthermore, the regression coefficient of the impact of digital input on the quality development of the manufacturing industry through the factor allocation structure is lower than that of the benchmark model, indicating that digital input improves the quality of the manufacturing industry by optimizing the factor allocation structure. Further promote the high-quality development of industry. Meanwhile, due to the differences in the development status of various regions, the regional heterogeneity between high schools in the east and west has weakened. The algorithm in this paper can effectively mine association rules for "different records contribute differently to association rules" and for data warehouses with large amounts of data. The algorithm reduces the I/O cost. In terms of the efficiency of using memory space to handle large databases, an ideal execution efficiency still needs to be achieved through an equal number of partitions.The next step will be to study the impact of digital investment on the high-quality development of the manufacturing industry from a national and regional perspective. The research can be extended to various industries in the manufacturing sector to increase the depth of analysis and make the research more comprehensive.

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