

Intelligent Investigation of Manufacturing Supply Chain Management System Based on Industrial Big Data

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In today's society, supply chain management systems are becoming more widely used, and their complexity is increasing. Suppliers and customers are distributed all over the world, leading to the traditional manufacturing supply chain management system being unable to operate optimally in the global context. Therefore, this current study uses industrial big data technology to examine the intellectualization of the manufacturing supply chain management system. Taking the supply chain management system of B manufacturing enterprise as an example, the study first determined the procurement process of the supply chain. Based on the comparison between common procurement quantities and actual demand results, it showed that the intelligent model of the system had stronger capture ability than traditional supply chain management systems, could timely understand market changes, and reduced procurement losses. The procurement volume was close to the actual demand. Secondly, the production process of the supply chain was examined. Based on the comparison of the total production quantity and qualified quantity results of the workshop within the specified time, it was found that the intelligent model of the system had higher production efficiency and quality every time compared to traditional supply chain management systems, especially with a production qualification rate exceeding 0.95 every time. Next, the warehousing process of the supply chain was examined. Based on the comparison of each count duration and the number of invalid counts, it was found that the total count duration of the system's intelligent model ranged from 30 minutes to 34 minutes, and the number of invalid counts for each experiment ranged from 1 to 5. The efficiency of each inventory was higher than that of traditional supply chain management systems. Finally, the logistics link of the supply chain was determined. Based on the comparison of logistics accuracy and logistics cost results, it was found that the logistics accuracy of traditional supply chain management systems was lower than 80%, while the logistics accuracy of intelligent system models was higher than 80%. The logistics costs generated by the intelligent system model were less than those generated by traditional supply chain management systems.

Keywords: supply chain management system; industrial big data; system intelligence; data acquisition and pre-processing; modeling analysis; decision support

1. INTRODUCTION

In the context of informatization, innovation in supply chain management has become a hot topic. In today's Industry 4.0 era, if enterprises want to achieve better development, they must improve their understanding of the intelligence of the supply chain management system, clarify its relationship

with industrial big data technology, and actively use industrial big data in the supply chain management system, so as to gradually accelerate the development of the manufacturing supply chain intelligence model based on industrial big data.

Traditional supply chains face problems such as uncertainty, high cost, high complexity, and high vulnerability of their operations. To solve these problems, it is necessary to improve the intelligence level of the supply chain man-

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agement system. Supply chain management is a relatively complex and massive system in enterprises, with many components. Taking the logistics supply chain of enterprises as an example, traditional logistics supply chain management poses significant competitive risks. Al Masri R examines the impact of green supply chain management practices on corporate sustainability performance [1]. Dash believed that the key to the success of physical enterprises lies in having a well-functioning supply chain management system, and proposed that using artificial intelligence to promote supply chain intelligence could reduce costs, increase revenue, and improve asset utilization [2]. Applying big data technology to supply chain management can enable the company to obtain more data and detailed analysis results, thus effectively improving the management ability of procurement, logistics, warehousing, logistics and other links, reducing the company's operating costs, and improving the accuracy of various decisions [3]. Aryal's research aims to provide insights into the understanding and implementation of disruptive technologies—specifically big data analytics and the Internet of Things (IoT) and explores the differences in research across supply chain and related fields regarding how disruptive changes are addressed and managed [4].

With the expansion of Industry 4.0, industrial big data has become a hot topic in the field of digital and intelligent industry [5-6]. Industrial big data is the most widely used data utilization technology in the current manufacturing industry. It has massive data resources and accurate problem-analysis functions. The application of industrial big data is very useful for process management and productivity improvement in the automation field. Complex drives and intelligent sensor systems can be easily optimized based on the information collected using this technology. Big data is the key to achieving system intelligence [7]. Abdirad elaborated that industrial big data was a concept focusing on system and process automation, digitization and industrial data exchange. Its goal was to achieve intelligent factories, shorten the delivery cycle of responding to customer needs or unforeseen events, and improve the productivity of the system. The application of this concept could improve manufacturing, supply chain management and logistics [8]. Maheshwari analyzed the role of big data analytics in supply chain management [9]. In short, industrial big data is very suitable for studying the intellectualization of supply chain management system in the manufacturing industry.

In the Internet age, the traditional supply chain management system has encountered bottlenecks in human resources, technology and management. Therefore, this present study built an intelligent model of the manufacturing supply chain management system based on industrial big data, after firstly ascertaining the main characteristics and problems of the current manufacturing management system. Based on the advantages of industrial big data technology, this paper proposes design ideas and implementation methods, and constructs a unified intelligent model through data collection and pre-processing, modeling analysis, and decision support. Finally, taking the supply chain management system of B manufacturing enterprise as the experimental object, the effectiveness of the system's intelligent model constructed in this paper was verified by comparing the results of the four

links: procurement, production, warehousing, and logistics with traditional supply chain management systems.

2. MANUFACTURING SUPPLY CHAIN MANAGEMENT SYSTEM

With the acceleration of global economic integration, China's manufacturing industry is facing increasingly fierce market competition. Therefore, how to better meet customer requirements, increase market share, and obtain larger profits at lower costs is an urgent problem to be solved. To achieve this goal, it is necessary to utilize a supply chain management system. Supply chain management emphasizes the formation of a strategic partnership through the collaboration between various nodes in the supply chain, so as to organically integrate and manage the supply chain inside and outside the enterprise, thereby achieving an overall optimization goal and achieving win-win results [10]. The system is based on suppliers, manufacturers, distributors, retailers and customers, establishing a complete network chain, and effectively managing logistics, information flow, and capital flow during this process [11-12]. Supply chain management is an integrated logistics management approach. Compared to logistics management, supply chain management has interactive characteristics and is an advanced form of logistics, which can improve management decision-making.

The manufacturing supply chain management system, as a complex and multi-dimensional system, involves multiple links such as suppliers, producers, distributors, etc. [13]. Its characteristics include the following:

(1) Coordination of information flow, logistics, and capital flow.

In the manufacturing supply chain management system, information flow is the means, logistics is the process, and capital flow is the condition. Figure 1 shows the coordination relationship between information flow, logistics, and capital flow. Effective coordination management plays a vital role in maximizing profits. Ultimately, the enterprise and its supply chain collaborate to meet the needs of the final customer.

(2) The complexity of supply and demand relationships

The core of supply chain management lies in the coordination between supply and demand relationships, which is not only the reason for supply chain management, but also its ultimate goal [14]. The supply-demand relationship in the supply chain also needs to ensure the accuracy of its goals, rapid responsiveness of actions, and high-quality service, which indicates the complexity of the supply-demand relationship in the supply chain.

(3) Diversity of supply chain nodes

Building a supply chain involves many aspects; hence, the node enterprises that make up the supply chain have different spans or levels. There are also many supply chains that are cross-border, cross-regional, and cross-industry combinations in the supply chain. A node enterprise can be a member of one supply chain or other supply chains.

(4) Uncertainty of supply chain operational risks

The uncertainty of operational risks in the supply chain generally varies with the characteristics of the product. Overall, the supply chain is a community of interests. However,

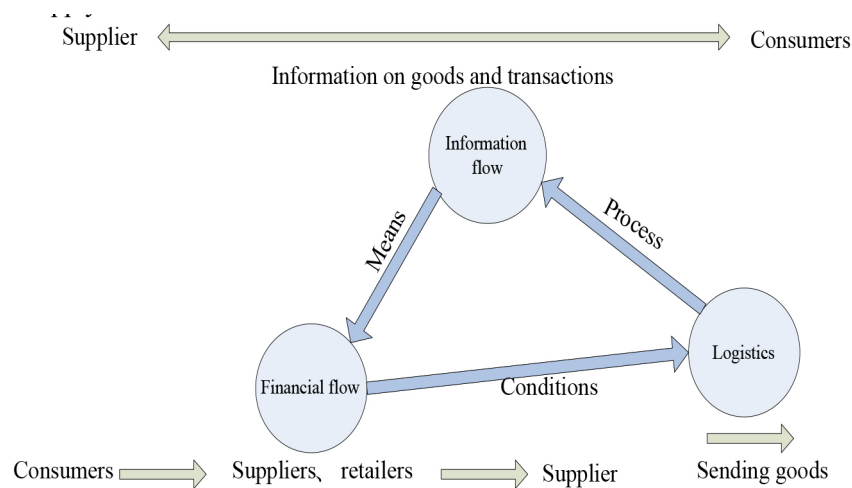


Figure 1 Coordination relationship between information flow, logistics, and capital flow.

companies in the actual supply chain are independent market participants with their own business strategy, operational level, technological level, target market, and unique corporate culture, all of which can increase the uncertainty of supply chain risks in the operation process.

In practical application, there are also problems with the manufacturing supply chain management system: First, in terms of product life cycle, the product lifecycle of manufacturing production is becoming increasingly shorter, placing greater pressure on manufacturing enterprises in scientific research. Only continuous technological innovation can meet the market demand. Second, in terms of sustainable development, the manufacturing industry must continuously improve its product quality despite the constraints of limited capital and resources, and strengthen product diversity in a resource-synergistic way to meet the personalized needs of customers. Third, in terms of market response, node enterprises in the supply chain often encounter incomplete and outdated information. Sometimes, during information exchange, many conflicts and delays may arise, making it difficult to convey customer demand information in a timely manner or respond quickly to the market. This leads to a lack of balance between supply and demand, ultimately resulting in customer dissatisfaction and loss of sales. In terms of synchronous decision-making, there may be a lack of trust and cooperation among node enterprises in the supply chain, which prevents real-time control of demand, supply, and inventory information in the supply chain. In addition, accurate business data is not collected in a timely manner, which cannot improve business operations and supply chain response speed, thus reducing the effectiveness of decision-making.

3. INDUSTRIAL BIG DATA TECHNOLOGY

3.1 Industrial Big Data

At present, big data is considered to be one of the most important fields of future technology, and has quickly gained the attention of many industries because it can provide high

value for enterprises [15-16]. An increasing number of enterprises are paying attention to the intelligence of supply chain management systems. Therefore, the introduction of industrial big data technology not only improves all links of the supply chain and optimize operation and services; it can also drive product innovation and modernize China's industrial sector [17]. Industrial big data is the key to achieving an intelligent manufacturing supply chain. The process of identifying and solving problems related to manufacturing supply chain management systems generates a large amount of data. These data can be analyzed and mined to discover the source of a problem, its impact, and a solution. In addition, data information is transformed into knowledge after being abstracted, which can be used to detect, solve and prevent problems. In other words, knowledge acquisition and problem-solving are goals, and industrial big data is the means.

In short, it no longer relies on human past experience, but instead seeks hidden clues in industrial data, enabling manufacturing knowledge to be more effectively and spontaneously generated, used, and inherited.

With the increasing complexity of manufacturing systems, industrial big data is used in the production process as a more effective and convenient tool. The goal of industrial big data is not to determine quantity; it is a systematic collection and analysis of data, as shown in Figure 2 in order to achieve maximum value. Therefore, the key to promoting the development of intelligent manufacturing is not industrial big data, but its analysis.

3.2 BP Neural Network

In recent years, the BP (back propagation) neural network has been continuously developing, and its application in supply chain management systems is also a current development trend. The BP neural network has outstanding self-learning ability, which can match the error of the network system with the accuracy required by the supply chain management system model. By continuously adjusting the module weight, it further reduces the error of the network system, making the

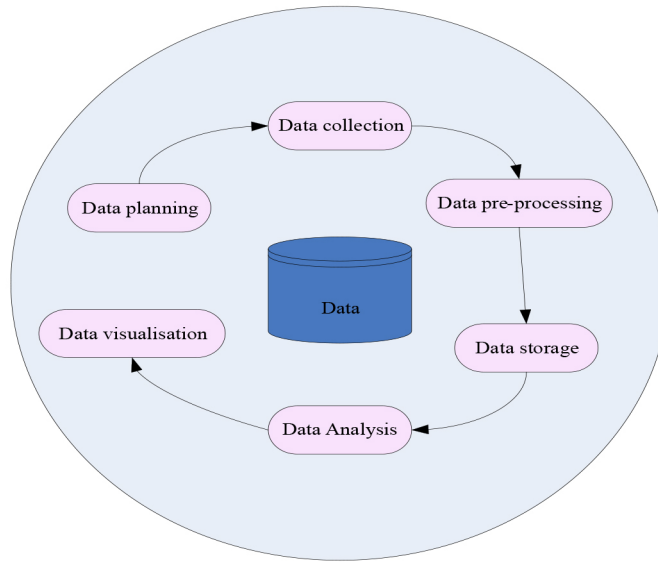


Figure 2 Basic framework of industrial big data analysis.

actual input to output direction of the network system closer to the target input-to-output value. The number of hidden neurons in the input layer and output layer of the BP neural network model can be calculated with Formula 1.

$$y = \sqrt{RC} \quad (1)$$

In Formula 1, y refers to the number of hidden layer neurons; R refers to the number of input layer neurons; C refers to the number of output layer neurons.

The formula for the output value of hidden layer neurons is as follows:

$$V_n^h = f^h \left(\sum_{g=1}^i w_{gn}^h Z_r + \forall_n^h \right), n = 1, 2, 3, 4 \quad (2)$$

where, w_{gn}^h refers to the connection weight from the g -th neuron in the input layer to the n -th neuron in the hidden layer; Z_r refers to the input vector of the input layer; r represents the number of input samples; $\forall_n^h$ is the hidden layer threshold.

The formula for the output value of the n th neuron in the output layer is as follows:

$$V_n^o = f^o \left(\sum_{g=1}^i w_{gn}^o V_n^h + \forall_n^o \right), n = 1, 2, 3, 4 \quad (3)$$

where, w_{gn}^o refers to the connection weight from the g -th neuron in the hidden layer to the n -th neuron in the output layer, and $\forall_n^o$ refers to the output layer threshold.

The formula for the error of the BP neural network model is:

$$S = \frac{1}{2} \sum_{g=1}^1 (Q_n - V_n^o) \quad (4)$$

4. DESIGN IDEAS AND IMPLEMENTATION METHODS FOR SYSTEM INTELLIGENCE

4.1 Data Collection and Preprocessing

1) Data collection

The key to the successful application of an intelligent supply chain management system is data collection. Cross-departmental data collection can help enterprises address issues in different areas of the manufacturing supply chain, enabling better data management and utilization. Taking the supply chain of manufacturing enterprise B as an example, the purchase quantities and actual demand of 9 different purchased goods in the procurement process of the supply chain are first collected, and then the production quantity and qualified quantity of the production process are collected. The collection conditions are selected as the experimental object in workshop 1, which is responsible for producing product A. The workshop has a total of 100 people, and the experiment duration is set at 6 hours. Then the inventory length and invalid inventory quantity of the warehousing link are collected. The spare parts warehouse of Manufacturer B is selected for inventory, of which there are 1000 samples. Finally, the logistics cost and logistics accuracy of the logistics link are collected. Product A of Workshop 1, Product B of Workshop 2, and Product C of Workshop 3 of Manufacturer B are selected as the experimental objects of the logistics link.

2) Data preprocessing

Data pre-processing involves data cleansing and data integration, which is intended to prepare for subsequent data processing. The process of data collection and pre-processing is shown in Figure 3. Firstly, the object of analysis is clarified: the four links of the supply chain of B manufacturing enterprise. BP neural network is used for feature extraction and classification of original data. The

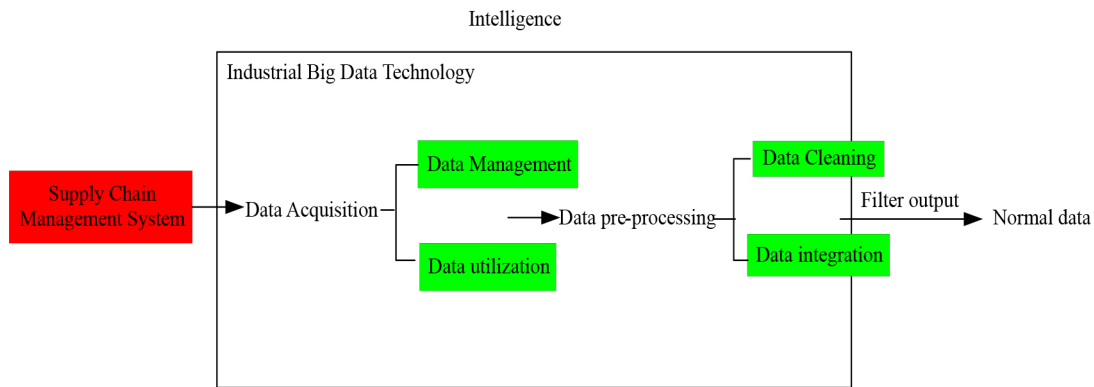


Figure 3 Flowchart of data collection and preprocessing.

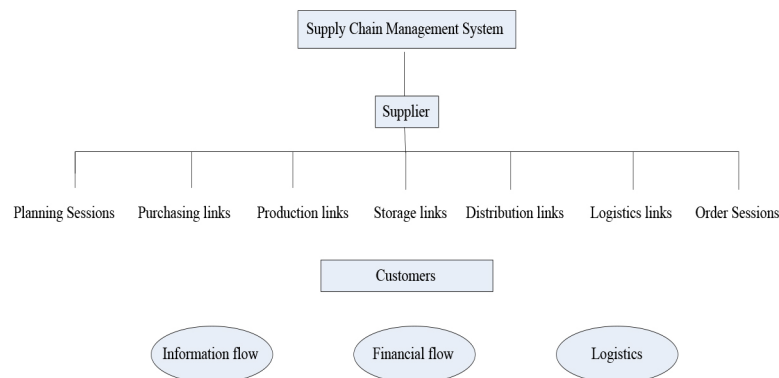


Figure 4 Intelligent model of supply chain management system based on industrial big data technology

collected link data is cleaned. The cleaned data is analyzed for scope, validity, and standardization, and applied to the actual scenario of the supply chain management system of B manufacturing enterprise. Combined with industrial big data technology, unstructured data is processed, and data quality is evaluated. Abnormal data is eliminated. Qualified data is integrated, and an analysis model is constructed.

4.2 Modeling Evaluation

Modelling analysis is a basic link in industrial big data technology. It is used to build analysis models such as machine learning and deep learning, so as to discover potential laws and future trends. The BP neural network is a core technology in the field of artificial intelligence. A BP neural network analysis model enables the computer to simulate the collected and preprocessed data and output the training sample set, so as to obtain a new set of performance indicators for the supply chain and apply it to achieve optimal solutions and intelligent decision-making. The complex supply chain relationship is modeled by means of a BP neural network analysis model, and an intelligent model of supply chain management system based on industrial big data technology is built to identify bottlenecks so as to improve the efficiency and accuracy of the supply chain.

4.3 Decision Support

In the real world, supply chain operations are full of uncertainty, so big data analysis is needed to help enterprises make intelligent decisions. By collecting a large amount of historical data from the supply chain of Manufacturing Company B, a supply chain data model is established to make accurate predictions and formulate plans. The planning involves constructing an intelligent decision optimization system for supply chain management in the B manufacturing industry in the supply chain data model to handle decision-making issues in various key areas of the supply chain. In order to solve typical decision optimization problems, an intelligent decision optimization system for B's manufacturing supply chain management is constructed, which includes multiple subsystems, including advanced planning and scheduling systems, warehouse management systems, transportation expert systems, and packaging expert systems. The daily activities of customers generally involve multiple key aspects of supply chain management, so they first combine their own pain points to effectively integrate customized intelligent decision-making subsystems, helping enterprises optimize the supply chain, improve production efficiency, and reduce costs.

On the basis of the above data collection, pre-processing, modeling analysis and decision support, the intelligent model of supply chain management system based on industrial big data technology is constructed, depicted in Figure 4.

Table 1 T1 purchase volume and actual demand for different commodities (Unit: pieces)

Commodities	Number of purchases	Actual demand	Difference
G1	1206	1000	206
G2	1530	1100	430
G3	1000	1200	-200
G4	1480	1300	180
G5	1207	1400	-193
G6	1239	1500	-261
G7	1730	1600	130
G8	1508	1700	-192
G9	2010	1800	210

Table 2 T2 purchase quantity and actual demand for different commodities (Unit: pieces).

Commodities	Number of purchases	Actual demand	Difference
G1	1000	1000	0
G2	1120	1100	20
G3	1200	1200	0
G4	1300	1300	0
G5	1401	1400	1
G6	1500	1500	0
G7	1602	1600	2
G8	1700	1700	0
G9	1802	1800	2

Figure 4 shows the relationship between suppliers and consumers at various stages of the supply chain, coordinated by information flow, logistics, and capital flow.

5. SYSTEM INTELLIGENCE EXPERIMENTAL VERIFICATION

The fourth part puts forward the idea and implementation method of system intelligence, and builds an intelligent model of supply chain management system based on industrial big data technology. In order to determine the effectiveness of the intelligent model of the supply chain management system, an experiment was conducted on the supply chain of manufacturing enterprise B. The traditional manufacturing supply chain management system was set as T1, and the intelligent model of the supply chain management system based on industrial big data technology was set as T2.

5.1 Procurement Process

There are many drawbacks in the traditional supply chain management method of procurement, if the purchaser and supplier have not yet established a close relationship. At the same time, the procurement management model cannot adapt well to the needs of the market, and customers, relying solely on its own inventory to complete product production, which has raised certain obstacles to the development of the enterprise. The intelligent model of supply chain management system based on industrial big data technology can adjust its own purchase plan and production plan in a timely manner according to customer demand and market

changes, and strengthen communication with suppliers during procurement to form a solid partnership, so as to improve its own procurement level and form a win-win development and cooperation mode with suppliers. As shown in Tables 1 and 2, 9 different procurement products of Manufacturing Company B were selected. The purchase quantity using T1 and T2, as well as the difference between the purchase quantity and the actual demand quantity, were recorded.

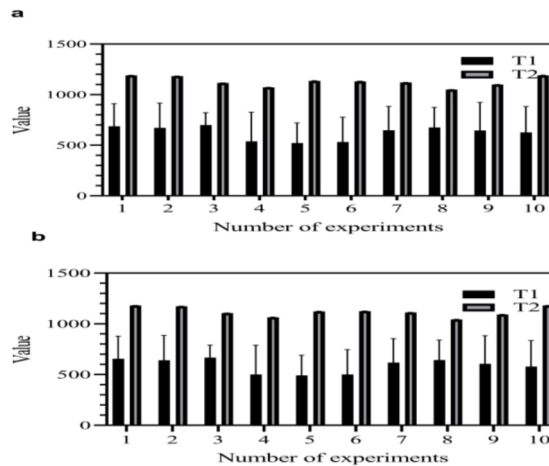
Table 1 shows the procurement volume and actual demand for 9 different goods of Manufacturing Company B under T1 operation. Among them, G2 has the largest difference between the purchase quantity and the actual demand, with an actual demand of 1100 pieces. However, Manufacturing Company B purchased 1530 items, which was a total of 430 extra items in inventory. The smallest difference between the purchase quantity and the actual demand was G7, which had an actual demand of 1600 pieces. However, Manufacturing Company B purchased 1730 items, resulting in an additional 130 items in inventory.

Table 2 shows the procurement volume and actual demand for 9 different products of Manufacturing Company B under T2 operation. Among them, G2 had the largest difference between the purchase quantity and the actual demand, with an actual demand of 1100 pieces. However, manufacturing company B purchased 1120 units, which added a total of 20 units to its inventory. The smallest difference between the procurement quantity and the actual demand was G1, G3, G4, G6, and G8, with actual demand of 1000, 1200, 1300, 1500, and 1700 pieces, respectively. The quantity of Manufacturing Company B's procurement was equal to the actual demand, and there was no excess inventory.

The purchasing unit price for 9 different products of Manufacturing Company B was 100 yuan per piece. Based on the data information in Tables 1 and 2, the purchasing cost

Table 3 Procurement costs and losses for 9 different goods of Manufacturing Company B under T1 and T2 (Unit: yuan)

Commodities	T1			T2		
	Actual demand costs	Purchasing costs	Losses	Actual demand costs	Purchasing costs	Losses
G1	100000	120600	20600	100000	100000	0
G2	110000	153000	43000	110000	112000	2000
G3	120000	100000	-20000	120000	120000	0
G4	130000	148000	18000	130000	130000	0
G5	140000	120700	-19300	140000	140100	100
G6	150000	123900	-26100	150000	150000	0
G7	160000	173000	13000	160000	160200	200
G8	170000	150800	-19200	170000	170000	0
G9	180000	201000	21000	180000	180200	200

**Figure 5** The total number of A Product and the number of qualified products produced after 10 experiments using T1 and T2 (Unit: pieces). (a) The total number of Product A produced using T1 and T2. (b) Qualified quantity of Product A produced using T1 and T2.

and actual losses could be calculated, as shown in Table 3.

Table 3 describes the procurement costs and losses of 9 different goods for Manufacturing Company B after using T1 and T2, respectively. T1's various products suffered significant losses. The loss of T2 was relatively small and could even be ignored. It could be seen that the intelligent model of the manufacturing supply chain management system designed based on industrial big data technology had strong exploration ability, could accurately predict the actual demand of the market, and reduced procurement costs and losses.

5.2 Production Process

The production link is important for determining the quality of manufactured products. The use of the latest industrial big data technology can enable intelligent configuration of the production and processing stages and avoid resource waste. After the raw materials used for production enter the workshop, they must be inspected, and those that do not meet the requirements cannot be used. In the procurement process, the materials have been coded and the relevant information has been input into the data processing platform. Therefore, in the production process, the materials that have passed inspection should also be coded and input into the data processing platform, as was done for the procurement process, so that the information about product materials can be traced back.

The No. 1 workshop of Manufacturing Company B responsible for producing Product A was selected as the experimental object, with a total of 100 people in the workshop. The experimental duration was set to 6 hours. The experiment involved operating in the No. 1 workshop using T1 and T2, and recording the number of products produced over 6 hours, each time under the two different systems, as well as the number of qualified products manufactured within the specified time. In order to reduce experimental errors, 10 separate experiments were conducted, as shown in Figure 5.

Figure 5 (a) depicts the total number of Product A produced using T1 and T2 through 10 experiments. In these 10 experiments, the total number of A Product produced by T1 each time ranged from 522 to 699. Among them, the highest total quantity of products produced within 6 hours was the third time, with a production quantity of 699. The minimum total quantity of products produced within 6 hours was the 5th time, with a production quantity of 522. In these 10 experiments, the total number of Product A produced using T2 ranged from 1050 to 1191 each time. Among them, the highest total quantity of products produced within 6 hours was the 10th time, with a production quantity of 1191. The minimum total quantity of products produced within 6 hours was the 8th time, with a production quantity of 1050.

Figure 5 (b) depicts the qualified quantity of Product A obtained by 10 experiments on T1 and T2. In these 10 experiments, the qualified quantity of Product A produced by T1 ranged from 492 to 667. Among them, within a 6-hour

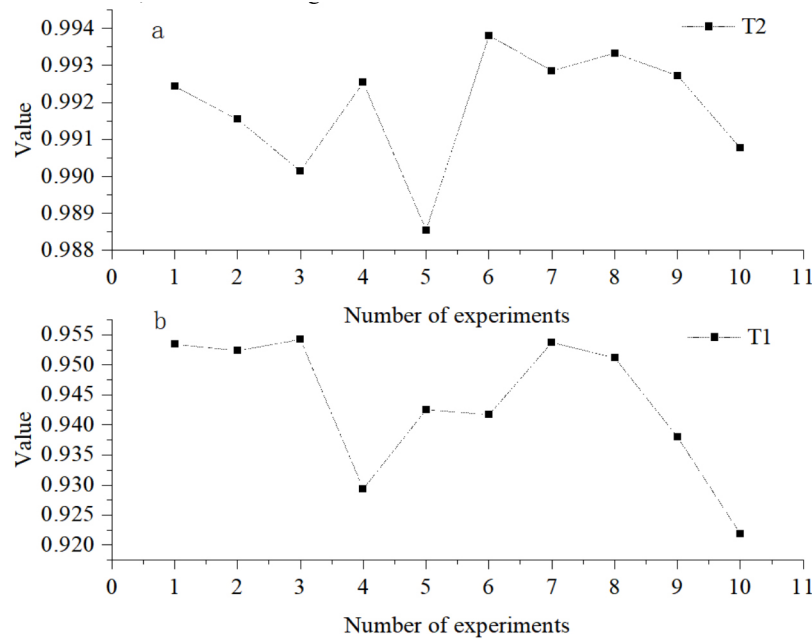


Figure 6 Qualification rate of Product A resulting from 10 experiments on different systems. (a) The qualification rate of Product A resulting from 10 experiments using T2. (b) Qualification rate of Product A resulting from 10 experiments using T1.

production time, the highest number of qualified products produced was the third time, with a qualified quantity of 667. The minimum number of qualified products produced was the fifth time, with a production quantity of 492. The qualified quantity of product A produced by T2 ranged from 1043 to 1181. Among them, the number of qualified products produced during the 6-hour production time was the first time, with 1181 qualified products. The minimum number of qualified products produced was the 8th time, with a production quantity of 1043.

Based on the data information in Figure 5, the qualification rate of Product A after 10 production experiments on T1 and T2 could be calculated, as shown in Figure 6.

It can be clearly observed from Figure 6 that in each experiment, the production qualification rate of T2 was higher than that of T1. The production qualification rate of T1 after 10 experiments was distributed between 0.922 and 0.954, with the highest qualification rate during the third experiment. There were 5 times when the qualification rate exceeds 0.95, and no more than 0.99 times. The production qualification rate of T2 after 10 experiments was distributed between 0.989 and 0.994, with the highest qualification rate during the 6th experiment. On 10 occasions, the qualification rate exceeds 0.95, the qualification rate exceeds 0.99 in 9 instances.

The comparison above shows that the intelligent model of supply chain management system built by industrial big data technology had good production performance, higher production efficiency and better production quality than the traditional supply chain.

5.3 Warehousing Process

In the traditional application of warehousing, the storage and inventory of the warehouse are all done manually, which is

time-consuming, labor-intensive, and prone to errors. The storage link of the intelligent supply chain management system is more digitalized and automated in inventory management, and the optimization of the past manual inventory counting operation is upgraded to an automated inventory counting supported by industrial big data technology.

The accessory warehouse of Manufacturing Company B was selected for inventory, with a total of 1000 samples. Under the same experimental conditions, T1 and T2 were used for 10 experiments, and the total inventory time and invalid inventory quantity were recorded, as shown in Table 4.

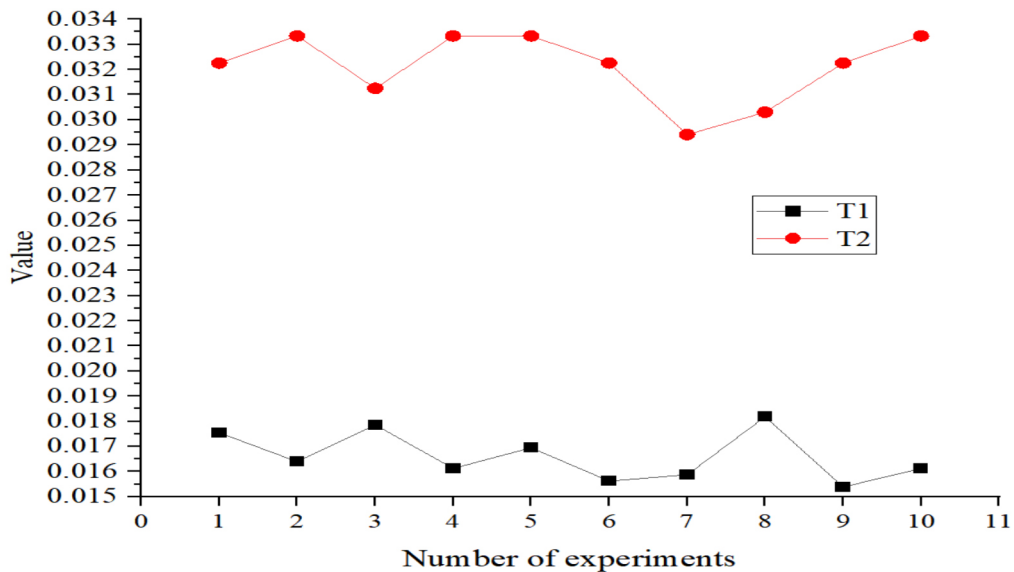
The total duration of T1 inventory recorded in Table 4 ranged from 56 minutes to 65 minutes. Six experiments were conducted with a total inventory time exceeding 60 minutes. In addition, the number of invalid counts for each experiment in T1 ranged from 16 to 21, while the total count duration for each experiment in T2 ranged from 30 minutes to 34 minutes. For four of the experiments, the total inventory duration was 30 minutes. In addition, the number of invalid counts for each T2 experiment ranged from 1 to 5. The experimental results for the warehousing process more clearly indicated that the inventory efficiency of T2 was much higher than that of T1.

Based on the total inventory duration and total sample count of T1 and T2 recorded in Table 4, the inventory efficiency yielded by 10 experiments was calculated. The efficiency was high with large values, as shown in Figure 7.

The trend of the curve in Figure 7 indicates that, on every occasion, the efficiency of T2 is higher than that of T1. T1 has the highest efficiency value of 0.0182, while T2 has the highest efficiency value of 0.0333. This shows that the use of industrial big data technology in the supply chain management system of the manufacturing industry can improve the efficiency and accuracy of inventory, and also see the inventory status accurately and in real time.

Table 4 10 total inventory duration and invalid inventory quantity for 10 experiments.

	Total time		Number of invalid stock	
	T1	T2	T1	T2
1	57min	31min	21	5
2	61min	30min	17	1
3	56min	32min	17	3
4	62min	30min	20	4
5	59min	30min	18	1
6	64min	31min	19	2
7	63min	34min	17	5
8	55min	33min	18	2
9	65min	31min	16	1
10	62min	30min	20	3

**Figure 7** Inventory efficiency values of T1 and T2 in 10 experiments.

5.4 Logistics Link

In the traditional manufacturing supply chain, logistics is an indispensable part of warehousing and transportation, raw material procurement, and goods sales. However, due to the untimely update of information in traditional supply chain management systems, logistics infrastructure and service capabilities are not strong, resulting in high operating costs. The intelligent manufacturing supply chain management system designed based on industrial big data can upload information related to logistics, such as inbound and outbound vehicles, transport path, transport mode, transport personnel, transport time and other information, to the data processing platform in real time, and conduct statistics and analysis of relevant information through the data processing platform.

The intelligent supply chain management system in the manufacturing industry can achieve visualization of basic logistics processes such as goods packaging, warehousing, transportation, loading and unloading, and distribution through on-board video monitoring, making it convenient for logistics management personnel to calculate, monitor, and analyze logistics data. If abnormalities are detected in

the data, it can timely activate the warning mode and better solve problems. The entire process is visualized, allowing customers to comprehensively query logistics information and facilitate cargo tracking.

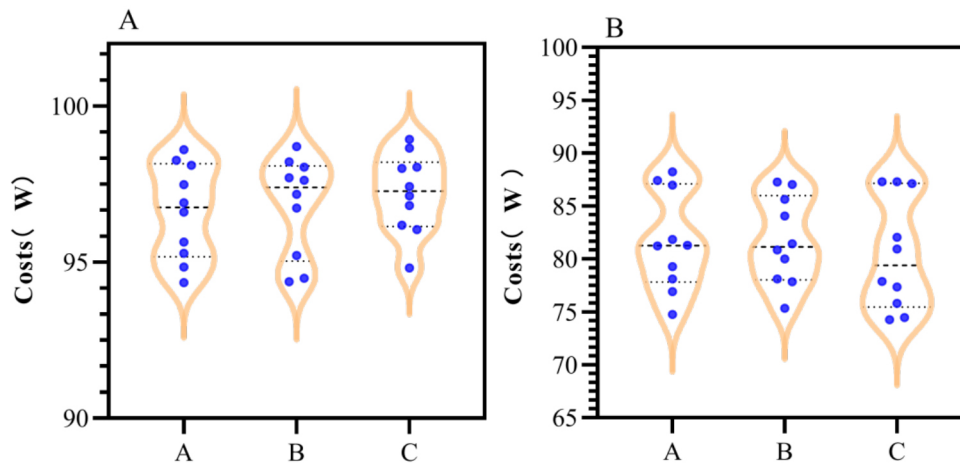
Product A from Workshop 1 of Manufacturing Company B, Product B from Workshop 2, and Product C from Workshop 3 were selected as experimental subjects for the logistics process. T1 and T2 were used to test the logistics accuracy and logistics costs of Products A, B, and C, as shown in Table 5 and Figure 8.

Table 5 records the logistics accuracy of using T1 and T2 for 10 experiments on Products A, B, and C. Among them, in the case of using T1 for logistics, the logistics accuracy of Product A was distributed between 55.25% and 76.68%, while the logistics accuracy of Product B ranged from 55.26% to 73.77%. The logistics accuracy of Product C ranged from 51.45% to 78.13%. Overall, the logistics accuracy using T1 was less than 80%, indicating a high probability of errors in the logistics process.

When using T2 for logistics, the logistics accuracy of Product A ranged from 80.82% to 96.63%, while the logistics accuracy of Product B was ranged from 84.93% to 99.32%.

Table 5 Logistics accuracy of T1 and T2 for 10 experiments on Products A, B, and C.

Number of experiments	T1			T2		
	A	B	C	A	B	C
1	71.95%	73.77%	73.10%	86.93%	95.50%	85.11%
2	76.68%	67.98%	76.14%	85.24%	90.13%	84.14%
3	55.25%	69.01%	53.40%	96.63%	95.83%	98.19%
4	57.50%	55.26%	51.45%	83.60%	92.06%	97.39%
5	58.69%	72.82%	71.12%	80.84%	88.79%	80.04%
6	75.48%	55.89%	78.13%	94.45%	86.38%	92.07%
7	58.78%	57.31%	70.77%	85.07%	84.93%	90.01%
8	76.09%	56.10%	57.96%	83.51%	99.32%	85.29%
9	74.83%	67.26%	59.20%	80.82%	91.57%	91.57%
10	66.13%	59.87%	52.01%	92.63%	94.77%	85.31%

**Figure 8** Logistics costs derived from 10 experiments on Products A, B, and C using T1 and T2. (A). Logistics cost of T1 for Products A, B, and C. (B). Logistics cost of T2 for Products A, B, and C.

The logistics accuracy of Product C ranged from 80.04% to 98.19%. Overall, the accuracy of logistics using T2 was higher than 80%, indicating a low probability of errors in the logistics process.

The comparison of accuracy results for T1 and T2 in Table 5 shows that the accuracy obtained by using T2 was higher than that of T1, and T2 had greater improvement than T1, with fewer logistics transportation faults.

Figure 8 presents the logistics costs incurred by the A, B, and C Products under 10 experiments using T1 and T2, while Figure 8 (A) shows the logistics costs incurred by T1 for 10 experiments on the A, B, and C Products. Among them, the logistics costs generated for Product A each time were concentrated between 943500 yuan and 986100 yuan. The logistics costs generated each time for Product B were concentrated between 943700 yuan and 987000 yuan, while the logistics costs generated each time for Product C were concentrated between 948200 yuan and 989400 yuan. Overall, it was found that the logistics costs incurred by T1 for Products A, B, and C remained between 940000 yuan and 990000 yuan.

Figure 8 (B) shows the logistics cost of T2 conducting 10 experiments on Products A, B, and C. Among them, the logistics costs generated each time for Product A were concentrated between 747600 yuan and 882300 yuan, and

the logistics costs generated each time for Product B were concentrated between 753500 yuan and 872800 yuan. The logistics costs generated for each C Product were concentrated between 742500 yuan and 872900 yuan. Overall, it was found that the logistics costs incurred by T2 for Products A, B, and C remained between 740000 yuan and 890000 yuan. From the figures and data, it can be observed that the logistics cost of using T2 was lower than T1. Therefore, T2 only improves the accuracy of logistics, but also reduces logistics costs.

In summary, intelligent supply chain management was more in line with the logistics requirements.

6. CONCLUSIONS

The Industry 4.0 era provides new development opportunities for society, including the improvement of manufacturing supply chains and the achievement of technological transformation and upgrading of supply chain systems. Therefore, it was valuable to study the intellectualization of a manufacturing supply chain management system based on industrial big data in this paper. The powerful data processing capability of industrial big data technology was used for data

acquisition and pre-processing, model analysis and decision support. For experimental verification, the supply chain management system of Manufacturing Company B was used as an example to compare the procurement, production, warehousing, and logistics aspects of the supply chain. The experimental results indicated that there was a small error between the procurement volume of the intelligent system model and the actual demand in the procurement process, which reduced the losses caused by traditional supply chain management systems. In the production process, the intelligent model of the system produced an increasing number of qualified products than did the traditional supply chain management systems, which further verified the particularly high production efficiency and quality of the intelligent model of the system. In the warehousing process, the system's intelligent model had a shorter inventory time, fewer invalid inventory quantities, and higher inventory efficiency. Regarding the logistics process, the accuracy of the system intelligent model was high, exceeding 80%. The logistics cost under the system intelligent model was low.

The research was based on industrial big data to achieve the intellectualization of the manufacturing supply chain management system, which is conducive driving market development, improving economic efficiency and promoting the development of enterprises.

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