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Analysis of Intelligent Replacement Strategies for Manufacturing Enterprise Jobs Based on Complex Networks

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Abstract

Responding to changes in job skill levels after the introduction of intelligent technology in manufacturing companies, starting from the perspective of complex network evolution, this paper first establishes the job division matrix of manufacturing enterprises, then analyzes the flow paths between different jobs by organizing and analyzing the network recruitment information of the enterprises, then establishes the job flow network model of manufacturing enterprises, and on the basis of this network model, it considers the changes in the job skills brought about by the introduction of intelligent technology in the enterprises, finally, taking an equipment manufacturing enterprise as an example, we analyze and compare the impact of adopting different job intelligent substitution strategies on the enterprise's job skills. The study found that the strategy of choosing to start the intelligent substitution of jobs from the production department can improve the overall job skill level of the enterprise, while the strategy of choosing to start the intelligent substitution of jobs from the sales department will reduce the overall job skill level of the enterprise, and choosing to start the intelligent substitution of jobs from the other departments does not have a significant effect on the overall job skill level of the enterprise.

Keywords: Post skills of manufacturing enterprises; Complex network; Job mobility model; Post intelligence strategy

1. Introduction

Nowadays, the deep integration of the digital economy and the real economy is pushing the manufacturing industry to transform into intelligent manufacturing, and different manufacturing enterprises are facing the impact brought by the new technology, due to the differences in market, technology, capital, etc., and adopting different coping strategies, which ultimately produces two distinctly different development paths---capital inclined or skills Tendency type[1].Capital-prone firms tend to use new technologies to replace workers' skills, which means that automation is used to reduce labor costs, increase output, and achieve lower product costs[2].Technology-oriented enterprises, on the other hand, use new technologies to expand workers' skills, which means that they constantly improve the value of their products in terms of product quality, product complexity and added value of the manufacturing process, with a view to obtaining higher profit margins. Most of China's manufacturing enterprises have been in the capital-oriented development path for a long time, which on the one hand, caused the continuous reduction of enterprise profit margins, and it is difficult to realize the continuous upgrading of the enterprise value chain through the accumulation of their own profits; on the other hand, a large number of positions within the enterprise have been replaced by automated equipment, and a large number of highly skilled labor force has been lost, which ultimately makes the enterprise lose its own talent reserves, and lack of independent innovation capability in the face of the new technological revolution. In the face of a new round of technological revolution, enterprises lack more independent innovation ability and have to further deepen their dependence on capital. Nowadays, with the advancement of artificial intelligence and other new technologies, the phenomenon of "machine for man" is being staged in various manufacturing enterprises[3].Manufacturing enterprises are faced with the urgent issue of how to formulate a reasonable intelligent replacement strategy for jobs in the era of intelligence, avoid the low-skilling of employees, and maintain and improve their own skill reserves and innovation capabilities.

In recent years, the phenomenon of changes in labor force skills due to technological progress has attracted the attention of a large number of scholars at home and abroad, and the theory of "Skill-Biased TechnicalChange" (SBTC)[4] has been established as a result. From the perspective of society's overall demand for labor, the theory suggests that technological progress increases the hiring preference of high-skilled workers and decreases the hiring demand of low-skilled workers. On this basis, Frey and Osborne analyze the risk of 702 occupations in the U.S. being replaced by intelligence and give the probability of each occupation being replaced by intelligence[5]. However, some scholars have argued that there is a substitution relationship between technological progress and high-skilled labor, and that technological progress in specific cases can instead lead to a weakening of workers' skills[6,7]. Acemoglu and Autor, on the other hand, analyse the impact of information technology on the United States job market and find that information technology has led to a rise in the demand for high-skilled and low-skilled labour and a fall in the demand for middle-skilled labour, i.e., the phenomenon of "job polarization"[8]. Many domestic scholars are also concerned about the impact of technological progress on employment trends in China, such as Sun&Hou[9]. verified the characteristics of China's labor force structure by region and found that regions with different levels of development in China present different employment structures, while Xie et al. found that AI significantly reduced the demand for low-skilled labor in China's manufacturing firms. Due to the long flow, complex technology and diverse personnel involved in modern manufacturing processes, it is inefficient to use traditional methods to analyze job mobility and skill changes in manufacturing companies. As a popular field in current research on complex systems, complex networks have been effectively applied in project risk analysis, system evolution analysis, and other research areas. Some scholars have also attempted to use complex networks to describe the impact of intelligence on occupational mobility and overall employment rates in society[10]. This article attempts to start from the perspective of complex network evolution, first constructing a network model for intelligent replacement of manufacturing enterprise positions. Based on this, the factors of intelligent replacement of positions and creation of new positions are introduced, and the possible impact of different paths of intelligent replacement of positions on the skill structure of enterprises is analyzed.

2. Analysis of Job Mobility Relationships and Intelligent Job Replacement Processes in Manufacturing Enterprises

2.1 Types of manufacturing company positions

As a pillar industry of the national economy, the manufacturing industry has many categories and complex varieties, in order to simplify the analysis process and clarify the relationship between job types and inter-job mobility, this paper refers to the classification of the national economy industry classification standard (GB/T 4754-2011) and the classification of the Occupational Classification Dictionary of the People's Republic of China (2015 edition) issued by the Ministry of Labor and Social Security, and after consulting with experts related to the manufacturing industry. The typical jobs are integrated and categorized, and a job division matrix is established to divide the typical jobs in manufacturing enterprises in horizontal and vertical directions, as shown in Figure 1:

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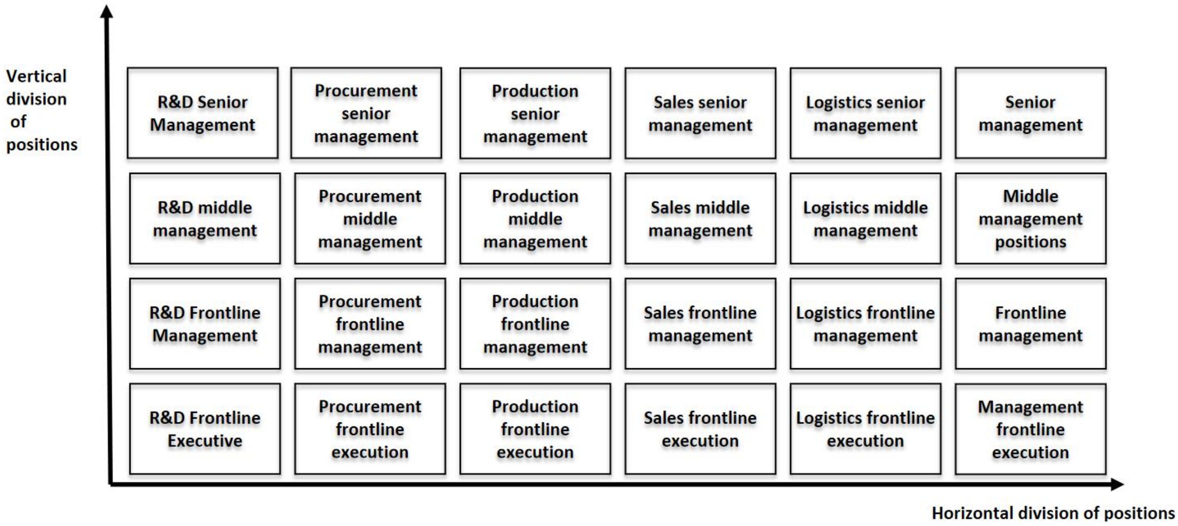

Figure 1 Job division in manufacturing enterprises

1) Horizontal division: Manufacturing enterprises usually divide their internal departments into several sub departments according to their own business needs, and undertake different work tasks, resulting in different types of positions. This article refers to the department settings of typical manufacturing enterprises and horizontally divides manufacturing enterprise positions into six categories: research and development positions, procurement positions, production positions, sales positions, logistics positions, and management positions.

2) Vertical division: Manufacturing enterprises will establish different management levels based on their size and number of employees. Considering typical management level divisions, this article vertically divides manufacturing enterprise positions into four levels: front-line executive positions, front-line management positions, middle-level management positions, and high-level management positions.

2.2 Job mobility relationships in manufacturing enterprises

Cross job mobility relationships arise between different positions due to similar skills and subordinate relationships. Job mobility is usually a one-way process, where low skilled positions move to high skilled positions due to skill accumulation and promotion, or to new positions due to business adjustments in the original position. Therefore the job flow relationship between job P_i and job P_j is represented using a directed edge pointing from job P_i to job P_j, as shown in Figure 2.

Figure 2 Cross job mobility relationship

Corresponding to the horizontal and vertical division of positions, job mobility also involves both horizontal and vertical mobility. For the vertical job mobility process, considering that the mobility across multiple levels in real enterprises is a rare event, this article only considers the vertical job mobility that advances one level at a time.

For the process of horizontal job mobility, the real reasons for job mobility within the enterprise are complex, often a two-way choice between individuals and positions, which is difficult to define with a unified factor. Here, the similarity of job skill requirements and business overlap are used as influencing factors to define the probability of job mobility. According to the revealed preference theory, a company's recruitment behavior reflects its talent demand[11], and the company's recruitment information fully reflects the skill requirements of the position. According to the job classification method given in Figure 1 for manufacturing enterprises, by organizing the recruitment information of representative companies in the manufacturing industry, the horizontal mobility

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relationship between each position is given based on the education, skills, and business requirements listed in the recruitment information, as shown in Figure 3.

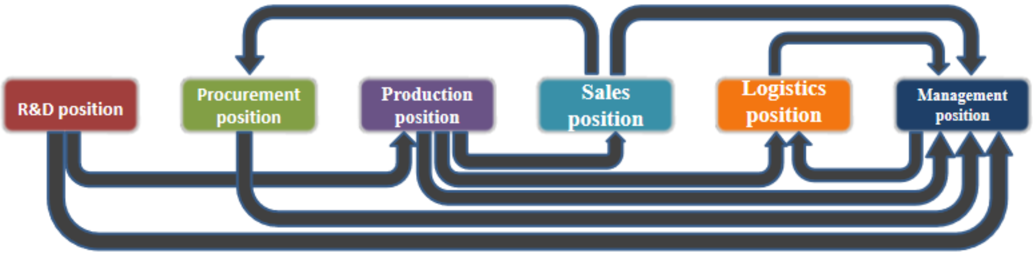

Figure 3 Horizontal job mobility relationship

2.3 Intelligent replacement of positions and creation of new positions

Due to the differences in educational level requirements, skill levels, and work complexity between different positions in manufacturing companies, there are differences in the likelihood of being replaced by intelligence Given the current level of intelligent development and the actual production of enterprises, it is difficult for the work tasks undertaken by senior management positions to be replaced by intelligence. Therefore, this article only considers the possibility of intelligent replacement for positions below the middle management level.By comparing and analyzing the job classification standards proposed in this article with existing research results, the corresponding risks of intelligent job substitution are obtained, as shown in Table 1：

Table 1 Probability of intelligent substitution for different positions

	R&D position	Procurement position	Production position	Sales position	Logistics position	Management position
top management	/	/	/	/	/	/
middle management	0.011	0.03	0.03	0.013	0.012	0.16
Frontline management	0.38	0.14	0.016	0.075	0.42	0.14
Frontline execution	0.68	0.29	0.85	0.25	0.37	0.31

After obtaining the probability of intelligent substitution for the corresponding position, it is necessary to determine the corresponding skill level of the position. Due to the significant differences in job content between different positions, it is difficult to directly classify skill levels based on job content. Here, we refer to relevant research on labor skill levels at home and abroad, and use the typical educational level of employees engaged in this position as the standard for dividing job skill levels. Positions with educational requirements of college diploma or above are classified as high skill positions, positions with educational requirements of high school or higher vocational education are classified as medium skill positions, and positions with educational requirements of high school or below are classified as low skill positions. Based on this, Table 2 is obtained for the classification of job skills in manufacturing enterprises.

Table 2 Skill levels of different positions in manufacturing enterprises

	R&D position	Procurement position	Production position	Sales position	Logistics position	Management position
top management	High skills	High skills	High skills	High skills	High skills	High skills
middle management	High skills	High skills	High skills	Intermediate skills	Intermediate skills	Intermediate skills
Frontline management	High skills	Intermediate skills	Intermediate skills	Intermediate skills	Low skill	Intermediate skills
Frontline execution	Intermediate skills	Intermediate skills	Low skill	Low skill	Low skill	Low skill

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At the same time as the original positions are replaced by intelligence, the phenomenon of information overload caused by the increase in enterprise information density has led to the emergence of new job demands in the process of intelligence[12], that is, the process of enterprise intelligence is accompanied by the replacement and creation of positions. This phenomenon has been widely studied by scholars and corresponding theoretical analyses have been established to analyze the skill changes in newly created positions[13]. Currently, it is believed that if new technologies improve labor productivity or reduce the cost of knowledge acquisition, the skills of workers in new positions will improve; If new technologies improve the communication requirements of positions or reduce communication costs, the skills of workers in newly added positions will decrease[14].

The changes brought about by the introduction of intelligent technology in different positions are not the same. For R&D positions, intelligent technology has led to a reduction in the cost of knowledge acquisition during the R&D process; Intelligent technology has led to an increase in labor productivity for production and logistics positions; The impact of intelligent technology on procurement, sales, and management positions mainly lies in reducing their communication costs. Therefore, considering the current direction of intelligent technology application in different positions, the skill changes of newly added positions after different positions are replaced by intelligence are shown in Table 3.

Table 3 Skill changes in newly added positions after being replaced by intelligence

Intelligent direction	Reduce the cost of knowledge acquisition	Reduce communication costs	Improve labor productivity	Reduce communication costs	Improve labor productivity	Enhance communication and specialization
top management	unchanged	↓	unchanged	↓	unchanged	↓
middle management	unchanged	↓	unchanged	↓	↑	↓
Frontline management	unchanged	↓	↑	↓	↑	↓
Frontline execution	↑	↓	↑	unchanged	↑	unchanged
Job category	R&D position	Procurement position	Production position	Sales position	Logistics position	Management position

3. Building a Complex Network of Job Mobility Relationships in Manufacturing Enterprises Facing Intelligent Substitution

3.1 Construction of a job mobility model for manufacturing enterprises based on complex networks

Currently, a large number of scholars have used complex networks to study labor mobility[15-17]. This article draws on Maria et al.'s modeling approach of using complex networks to study the impact of automation on the long-term unemployment rate in the US labor market , and establishes a manufacturing enterprise job mobility network model. The points in this network model represent characteristic positions, and the edges connecting the two points represent the flow relationship between two related positions. For a specific position, possible mobility relationships include higher-level mobility relationships within the same department, mobility relationships between different departments with the same job content, and mobility relationships between different departments with work associations. The possible mobility situations are shown in Figure 4.

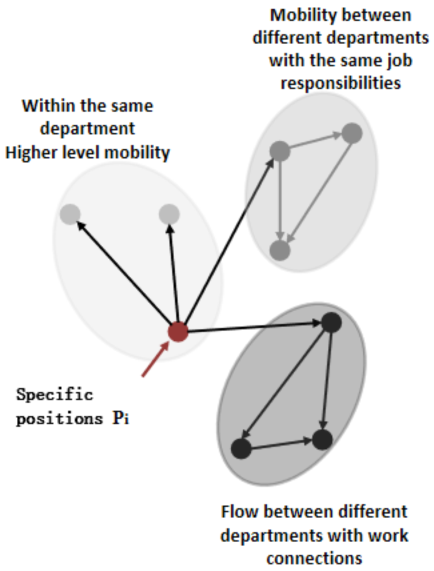

Figure 4 Specific positions P_i job turnover situation

Among them, the higher-level mobility relationships within the same department can be obtained through the vertical division of positions in Figure 1. For the convenience of research, only the mobility from low to high position levels is considered, and the position level can be increased by up to one level at a time of mobility; For job mobility between different departments with the same job responsibilities, in order to simplify modeling, it is assumed that positions with the same job responsibilities have consistent mobility possibilities between different departments, meaning there is no tendency to choose a specific department; The job mobility relationships between different departments with work associations are given in section 2.2 above, and only the job mobility relationships with lower to higher levels and a maximum increase of one level at a time are considered during job mobility.

3.2 Intelligent substitution of positions and creation of new positions

On the basis of the initial network model of job mobility in manufacturing enterprises obtained by the above method, intelligent technology factors are introduced. Simultaneously considering the role of job substitution and job creation brought about by the advancement of intelligent technology [15], dynamically update the network model. Let the initial time be t_0, only one process of intelligent replacement and creation of positions occurs per unit time; if at time t_0 position P_0 replaced by intelligent technology, positions P_l to the position P_n all exist in relation to the position P_0 , then at time t_1 , the probability of position P_l being replaced by intelligence should meet:

$$p_l = max\, p_{l\sim n} \quad and \quad p_l \geq p_0 \tag{1}$$

In the formula, $p_{l\sim n}$ represents the probability of position $P_{l\sim n}$ being replaced by intelligence,which is given in Table 2.Due to the limitations of intelligent technology, there is a threshold for the probability of a position being replaced by intelligence p_0,positions with a probability below this threshold will not be replaced by intelligence.

Intelligence will create new job demands while replacing specific positions.Let intelligent technology replace positions as P_k at time t_k,the number of employees engaged in this position is k,the number of employees engaged in the newly added positions at time t_{k+1} is $P_{\hat{k}}$:

$$\hat{k} = \varepsilon k \,, 0 \leq \varepsilon \leq 1 \tag{2}$$

In the formula, ε is defined as the coefficient of intelligent job creation,due to the improvement in labor productivity brought about by the application of intelligent technology, for a specific job ε is a coefficient between 0 and 1, which means that the demand for new employees created by intelligent technology will not exceed the demand for the original employees it replaces.

4. Example Analysis

Taking a certain equipment manufacturing enterprise Z as an example, analyze and verify the effectiveness of the model method proposed in this paper. Z Enterprise is a well-established large state-owned enterprise, mainly engaged in the research and development, production, and sales of special machinery and equipment. Due to historical legacy and other reasons, the job positions are redundant and the overall skill level of employees is low, resulting in Z enterprise currently facing problems such as low technological innovation capability, insufficient product competitiveness, and declining market share year by year. To overcome the current difficulties, Z Enterprise plans to introduce intelligent technology to replace some positions, in order to enhance the company's skill level and strengthen its own technological innovation capabilities.

4.1 Enterprise job mobility model based on complex networks

Z company has a total of 24 sub departments. By sorting out the work content of different positions and merging similar positions, 89 types of positions in Enterprise Z are obtained.Classify the jobs in Enterprise Z in conjunction with the classification methodology in section 2.1 of this paper, and determine the flow relationships between the jobs in accordance with section 2.2 of this paper. Gephi network analysis software was used to analyze the results. In order to facilitate the comparison of the positions occupied by positions with different skill levels in the network, Fruchterman Reingold (FR) algorithm was used to adjust the network layout, and the Z company's position flow network diagram was obtained as shown in Figure 5.

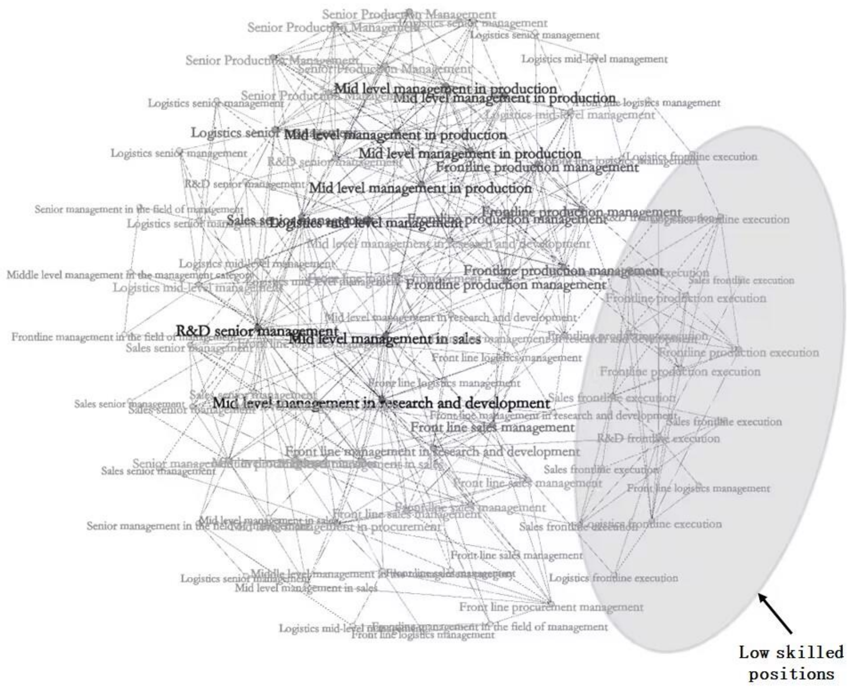

Figure 5 Z Enterprise job mobility network diagram

According to the job skill classification criteria given in Table 3, it was found that there is a significant difference in network location between low skilled and high skilled positions in Company Z. Low skilled positions are concentrated at the bottom right edge of the network and have less connection with medium and high skilled positions. Due to the fact that the connections between positions in the network model represent the similarity of skills between positions, the analysis of job mobility in Z enterprise shows that there is a significant skill difference between low skilled positions and other positions in Z enterprise, with a single role in the production process and gradually being marginalized.

4.2 Changes in the number of enterprise positions under intelligent substitution strategies for different positions

The impact of current advances in intelligent technology on manufacturing enterprises is no longer limited to the production process, but has permeated the entire business process. For manufacturing enterprises, due to limitations in funding, technological capabilities, and other factors, it is generally difficult to intelligently replace all positions at the same time. Instead, they need to choose from multiple intelligent replacement strategies for positions, and different choices of job intelligence strategies can ultimately lead to a fundamental difference between jobs that are replaced by intelligence and jobs that are added to the organisation, thereby affecting the overall number of positions, skill levels, and innovation capabilities of the enterprise.

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The initial intelligent replacement positions are R&D, procurement, production, sales, logistics, and management, respectively, to represent the different intelligent replacement strategies adopted by Z enterprise, denoted as strategies 1-6. Perform evolutionary analysis on the job mobility model of Company Z using the method provided in Section 3.2. According to the probability of intelligent substitution in Table 2, the likelihood of front-line execution positions being replaced by intelligent substitution is greater than that of other positions. Therefore, front-line execution positions are the initial positions for intelligent substitution of various strategies. According to equations (1) and (2), the substitution and addition of positions are achieved, and the substitution coefficient ε is taken 0.5, threshold for job substitution $p_0 = 0.1$. After the current position is replaced by intelligence, select the next stage of intelligent replacement position according to equation (1), and when the probability of position replacement is below the threshold p_0, at this point, the substitution process terminates. The changes in job positions in Z company after selecting intelligent replacement strategies for different positions are shown in Table 4.

Table 4 Changes in the number of positions in Z enterprise caused by intelligent substitution strategies for different positions

		Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6
Positions replaced by intelligence	High skills	80	19	19	0	19	22
	Intermediate skills	11	70	54	192	54	54
	Low skill	583	88	671	88	88	88
	total	674	177	744	280	161	164
New positions added	High skills	35	27	292	27	27	27
	Intermediate skills	303	54	54	44	54	56
	Low skill	0	8eight	0	67	0	0
	total	338	89	346	138	81	83
Change in the number of positions		-336	-88	-398	-142	-80	-81
Total number of positions		769	1017	707	963	1025	1024

It can be observed that due to the existence of the intelligent substitution coefficient ε, in the process of intelligent transformation of their own positions, regardless of which strategy they choose, the overall number of positions will decrease. However, the degree of job decline caused by different strategies is not consistent, with the most significant decrease in the number of positions caused by choosing intelligent replacement of production positions, and the least significant decrease in the number of positions caused by intelligent replacement of logistics positions.

4.3 Changes in job skills and innovation capabilities of enterprises under intelligent substitution strategies for different positions

Comparing the initial job situation of Company Z, it can be seen that when the company adopts different intelligent replacement strategies for positions, the number and proportion of different skill positions are different. The specific trend of change is shown in Figures 6 and 7:

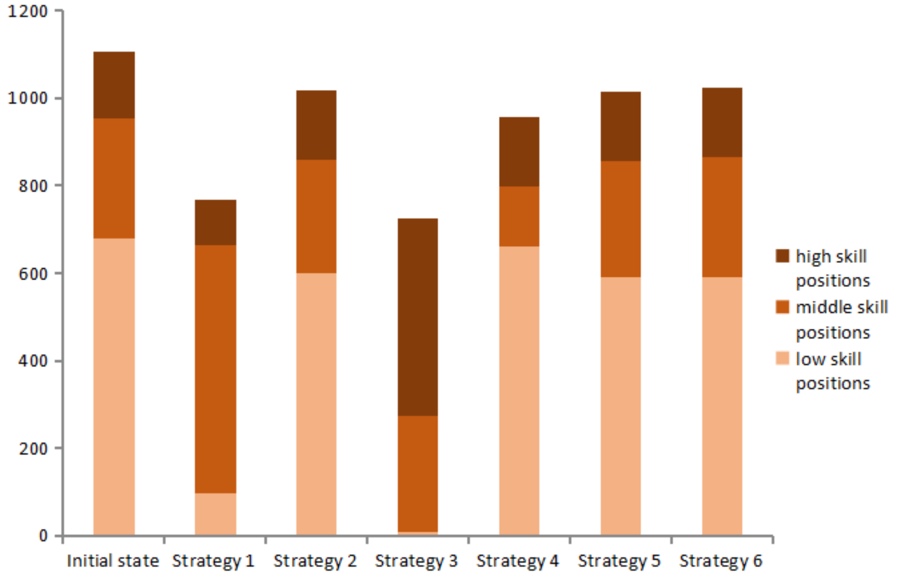

Figure 6 Number of skilled positions in enterprises after intelligent substitution

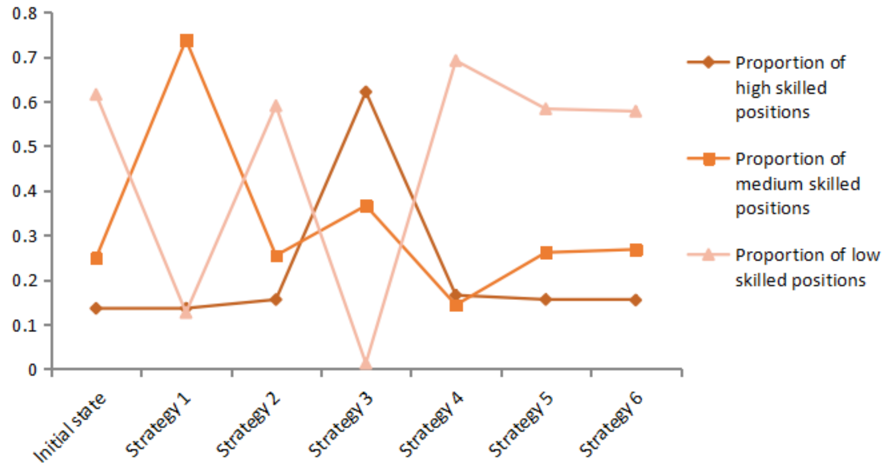

Figure 7 Proportion of various skill positions in enterprises after intelligent substitution

It can be observed that when Z company chooses different intelligent replacement strategies for different positions, the trend of changes in the proportion of different skill positions to the total positions is not consistent：

1)If a company chooses to initialize and replace its sales department, it will lead to an increase in the proportion of low skilled positions, a decrease in the proportion of medium skilled positions, and a basically unchanged proportion of high skilled positions, ultimately resulting in a decrease in the overall skill level of the company's positions;

2) If a company chooses to initialize alternative production departments, it will reduce the proportion of low skilled positions and increase the proportion of medium and high skilled positions, resulting in an overall improvement in the skill level of the company's positions;

3) Choosing to initialize and replace the R&D department will increase the proportion of medium skilled positions and decrease the proportion of high skilled positions, while choosing to initialize and replace the procurement, logistics, and management departments has no significant impact on the skill level of enterprise positions.

Currently, it is widely believed that the increase in the number and types of high skilled positions in enterprises will have a positive promoting effect on the technological innovation capability of enterprises. Without considering other external factors, taking the total number and types of high skilled positions as the influencing factors of the technological innovation capability of enterprises, the impact of different intelligent substitution strategies for positions on the technological innovation capability of Z enterprise is shown in Table 5

Table 5 Changes in Z enterprise's technological innovation capability caused by intelligent replacement strategies for different positions

	Initial state	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6
Total number of high skilled positions	153	105 ↓	158 ↑	450 ↑ ★	158 ↑	158 ↑	158 ↑
Number of types of high skilled positions	40	39 ↓	46 ↑	55 ↑ ★	48 ↑	46 ↑	44 ↑
Enterprise technological innovation capability	/	decline	promote	promote	promote	promote	promote

In summary, if Z company hopes to improve its job skills and enhance its technological innovation capabilities through the introduction of intelligent technology, prioritizing the intelligent technology transformation of the production department is an effective way to achieve this goal. If other departments are prioritized for transformation, it will be difficult to achieve the overall improvement of the company's job skills and technological innovation capabilities.

5. Conclusion

With the continuous deepening of the impact of intelligent technology on the manufacturing industry, how intelligence will affect the job skills of manufacturing enterprises is increasingly receiving attention. This article proposes a new method for finding a replacement path for intelligent job positions in manufacturing enterprises based on complex network related theories, in order to better guide enterprises in carrying out job intelligence reforms. The main steps of this method are: 1) Classify the types of positions in manufacturing enterprises and calculate the probability of intelligent substitution for different positions; 2) Analyze the mobility relationships between different positions; 3) Construct a manufacturing enterprise job mobility network model based on complex networks, with nodes representing positions and edges representing inter position mobility relationships; 4) Introducing factors of job intelligence substitution and new job creation into network model nodes, considering the transmission effect of job intelligence process between adjacent network nodes, analyzing the impact of job intelligence substitution order on the overall job skill level in the network model, and determining the preferred job intelligence substitution strategy for enterprises when adopting different development strategies. Finally, taking a certain equipment manufacturing enterprise as an example, the effectiveness of this method was verified.

The current method treats the manufacturing enterprise itself as a closed network, without considering the impact of external market environment, policies and regulations on job intelligence. At the same time, the division of job skills has not been further refined. The next step is to establish an open network model that considers external environmental factors based on previous research, and further refine job skills for different manufacturing types, in order to better guide the decision-making process of enterprises.

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