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Three-Dimensional Synergies: The Impact of Intelligent Investment, Industrial Environment, and Human Capital on the Employment Structure of High-Tech Manufacturing

***Jing Guo* [1,*], *Weikang Nie* [2]**

[1] Beijing University of Posts and Telecommunications, Beijing, China, 100876
[2] Zhejiang University of Finance & Economics, Zhejiang, China, 310018

[*] mailguojing@bupt.edu.cn

Abstract. This study investigates the impact pathway and mechanisms of multi-factor artificial intelligence investment on the proportion of high-tech manufacturing labor force, drawing upon the theory of skill-biased technological changes (SBTC). Employing a mixed qualitative and quantitative research design, we identify key resource factors influencing changes in the employment structure within the high-tech manufacturing industry. Our analysis employs fuzzy-set qualitative comparative analysis (fsQCA) on a provincial dataset from China, spanning the years 2018 to 2020. Findings reveal the following insights: (1) There exists a configurational effect among antecedent factors influencing changes in the employment structure of the manufacturing industry. Specifically, investments in AI-related industries, industrial robots, industry transformation and upgrading, industrial intelligence, working-age population proportion, and educational attainment of the workforce are not individually necessary conditions. (2) There are three paths that drive the increase of the proportion of high-tech manufacturing labor force, including comprehensive development type, capital-led type, and education-led type. (3) Investments in industrial robots and advancements in industrial intelligence emerge as pivotal factors driving the increase in the proportion of high-tech manufacturing labor force. This research contributes to advancing a multidimensional perspective on biased technological change, laying the groundwork for regional management strategies to invest in AI for fostering the healthy development of high-tech manufacturing.

Keywords: technological progress, artificial intelligence, high-tech manufacturing, employment structure, configurational effects, fsQCA

1. Introduction

Technology is the key factor to achieve productivity goals, talent is the basic resource to drive social progress and development, and innovation is the main driving force to drive social progress and development. High-Tech manufacturing is an industry with high technology content and high added value, an important part of the national strategic emerging industries and a key part of building a modern industrial system, which profoundly affects the core competitiveness of the country. The widespread application of artificial intelligence-related technologies, products and equipment in the manufacturing industry has profoundly changed the job demand of high-tech manufacturing industry [1]. For example, the popularity of industrial robots has formed direct job competition with workers, which on the one hand will transform the original jobs in production lines and put forward higher skill demands for workers. On the other hand, it will also replace some repetitive and codable routine tasks and increase the demand for human-machine collaborative jobs. At the same time, AI inputs also attract more highly skilled and educated talents, transforming the talent structure in the industry at the supply level. Nowadays, the optimization of employment structure in high-tech manufacturing industry has been faced with new challenges and opportunities. How to maintain a reasonable employment structure of high-tech manufacturing industry and ensure the healthy and sustainable development of high-tech manufacturing industry has become a topic of great concern. At the same time, the labor market supply in China has entered the stage of negative growth normalization, and the new situation of labor resource supply makes the main reason for the change of employment structure in manufacturing industry change, covering more factors other than capital deepening and industrial intelligence. The proportion of talents with higher education in China is increasing, more graduates with higher education will also become an important driving force to support the development of high-tech manufacturing industry. At present, the supply of China's labor market has changed from the "demographic dividend" to the "talent dividend". How to identify the multi-factor influence mechanism of AI application on the employment structure of high-tech manufacturing industry and find the appropriate path to import talent dividend to high-tech manufacturing industry has become a research problem of both practice and theory [2].

Existing studies have pointed out that technological progress provides an important perspective to analyze the structural problems of labor force employment, and technological advances in artificial intelligence will generate both job substitution and creation effects. Among them, the creation effect is reflected in the fact that technological progress can stimulate consumer demand and expand the production scale of enterprises, thus creating more job opportunities and job demand [3]. The substitution effect refers to the fact that technological advances will replace the job content or skills of the labor force, leading to a decrease in the demand for labor in enterprises and causing structural and technological unemployment [4]. Some scholars also believe that the impact of AI on employment is divided into substitution effect, productivity effect, and industrial structure effect [5]. The substitution effect will lead to an increase in unemployment; the productivity effect will promote increased capital accumulation and economic growth, creating more employment opportunities; the industrial structure effect refers to the development of AI technology will change the relative benefits and costs between different industries, leading to the expansion and contraction of some industries, thus changing the employment structure. Further, the superposition of the three effects will lead to social and economic differentiation, i.e., the gap between high-skilled, high-income people and low-skilled, low-income people will increase, the middle-skilled, middle-income people will decrease, and the polarization effect of employment structure will occur.

These studies have provided sufficient theoretical basis for analyzing the structural change of manufacturing employment, however, most of the existing studies have explored the “net effect” correlation of individual factors, ignoring the joint effect between different levels and multiple factors. The structural change of labor force employment is a complex process of multifactor joint constraints and correlations, and there are overall and internal correlations and interactions. This traditional regression analysis method of probabilistic model is difficult to explain the complex causality, and there may be substitution or complementary effects among various influencing factors in the model, i.e., the endogeneity of variables in the multi-factor model cannot be fundamentally resolved. Moreover, the antecedents affecting the employment structure have functional similarity among them, and there are certain substitution relationships, as well as multiple equivalent causal chains of the same path. More importantly, it is of more managerial and practical significance to explore the path to channel the talent dividend into high-tech manufacturing industry from the multi-factor supply of artificial intelligence input, industrial environment change, and labor market talent supply, and to find out the necessary conditions to promote the increase of employment in high-tech manufacturing industry. Based on this, this paper uses the fuzzy qualitative comparative analysis method in fuzzy mathematical theory to try to control the correlation and interaction between multiple factors and effects, and adopts a mixed research design combining qualitative and quantitative to improve the scientific and accuracy of the conclusion. Finally, this paper focuses the research problem on the high-tech manufacturing industry in the manufacturing industry, and explores the effect of AI technology advancement on the employment structure of the group, in order to clarify the mechanism of AI technology advancement on the change of employment structure in the high-tech manufacturing industry, and promote the transformation from a single perspective to a multidimensional perspective in analyzing the effect of AI technology on the change of employment structure.

2. Theoretical Basis and Literature Review

2.1. Historical Evolution of The Impact of Technological Progress on Employment

The relationship between technological progress and employment has been one of the focal issues in economics and management research. The theory of technological progress is also considered to be the theory that best explains changes in the structure of employment apart from international trade theory and outsourcing factors [6]. Schumpeter (1934) proposed that the adoption of new technologies would destroy relatively degraded units of production and that this process of creative destruction would result in firm bankruptcy and worker unemployment. However, innovation at that stage still fell under the conceptual umbrella of technological innovation. from the 1950s to the 1970s, technological progress was considered the main driver of job creation, emphasizing its positive impact on employment. In the late 1980s, a large number of valuable products and services were considered to be the result of technological innovation, while new technologies could also weaken, fragment or make jobs more dangerous. During this period, researchers divided technological progress into “process innovation” and “product innovation” and explored their different effects on employment. Since the 1990s, with the continuous development of information and communication technologies, the forms of technological progress have been innovated and the mechanisms of their effects on the employment structure have become more complex [7]. The consensus conclusion is that technological progress can directly affect the structure of employment and mainly indirectly by causing industrial restructuring and thus employment structural changes.

The development of globalization in the early 21st century has contributed to innovations in the theory of technological progress. Autor (2003) found that computerization replaces workers in performing cognitive and manual tasks with well-defined rules, and in performing non-procedural problem solving and complex communication tasks complemented workers, and that computerization was associated with reduced labor inputs for routine manual and routine cognitive tasks and increased labor inputs for non-routine cognitive tasks [8]. This study showed that technological advances affect jobs and thus employment opportunities. During the same period, Acemoglu (2002) suggested that skill-preferring technological advances would increase the demand for quantitative skilled labor and decrease the demand for low-skilled labor, while skill-degrading technological advances would increase the demand for low-skilled labor [9]. In recent years, technological change has become more rapid, and researchers have begun to explore the impact of AI on employment based on the theory of technological progress, exploring industrial robot inputs and the scale of AI investments, analyzing the substitution effect, productivity effect, and industrial structure effect of their new technologies on the job market [5], predicting the types of jobs that will be replaced by AI and the number of them [10], and summarizing the how AI can create more efficient work processes, higher quality products, and enable faster innovation, and analyzed how AI would change the employment demand and job opportunities in different industries.

2.2. Theoretical Mechanisms of Technological Progress in AI Affecting Employment Structure

The impact of AI technology progress on the employment structure is divided into three aspects including the impact on industry allocation, job quantity and job demand, see figure 1. Firstly, in terms of affecting the allocation of industries, AI technology has less impact on agriculture, but manufacturing is the industry most affected by AI technology, because the production technology characteristics of this industry itself make it more vulnerable to the substitution effect of AI technology. In a study conducted by Acemoglu, they analyzed the impact of industrial robot inputs on the U.S. labor market between 1990 and 2007 by building a regression model. Based on the empirical results, they inferred that the number of unemployed in manufacturing due to the use of industrial robots during this period could reach between 360,000 and 670,000 [5]. In contrast, among the service sector, jobs in the service industry require higher social skills and are not easily replaced by AI. Deming noted that the number of socially intensive jobs in the US increased by 24% between 1980 and 2012, while the share of employment increased by 7.2%, indicating a continuous growth in demand in the service sector [11]. In addition, some researchers have pointed out that the development of AI technologies will further generate new job demand in the service industry. For example, Frey et al. (2017) used a computerized risk model to predict the impact of AI technologies on different occupations [4].

Secondly, in terms of the effect of AI on the number of jobs, most scholars believe that AI technologies have both job replacement and creation effects. In terms of the substitution effect on the number of jobs, Frey and Osborne in their 2017 study measured the probability of computer substitution for 702 specific jobs using Gaussian classification algorithm and found that about 47% of jobs in the United States have the possibility of being replaced by computers [4]. And Frey found a significant negative correlation between education level and the probability of being replaced by robots. Also, some scholars have studied the relationship between education and employment and found that the higher the educational level of the workforce, the easier it is to be competent in positions with high cognitive skills and high information technology skill requirements. When educational attainment in the labor market increases, there is a relative increase in the employment of high-skilled labor and a relative decrease in the employment of low-skilled labor. Arntz (2017) studied the degree of job automation substitution in 21 OECD countries and found that about 9% of jobs in the United States have a probability of automation substitution higher than 70% [12]. David (2017) assessed the Japanese labor market and found that about 55% of jobs in Japan are vulnerable to replacement by smart computers and that informal jobs are more vulnerable [13]. On the creation effect of the number of jobs, Gordon (2014) argues, based on historical experience, that AI technology does not trigger mass unemployment and that technological progress itself is a source of job creation. Using a theoretical model, Acemoglu explores the mechanism of the impact of automation on the job market and finds that while automation eliminates some jobs, it also gives rise to some new jobs that are jobs are more suitable for human workers to exploit their comparative advantages [14]. Acemoglu also found an overall negative correlation between corporate industrial robots and employment, with its further reduction in the number of jobs. In addition, other scholars have considered the impact of population aging on the labor market, suggesting that as the population ages, the labor supply decreases, which may offset the negative impact of AI technologies on labor demand. It has also been suggested that population aging will reduce the labor force participation rate [15], and that the high proportion of elderly people will result in more service sector employment than manufacturing employment [16].

Thirdly, the labor and employment impact of AI is not only reflected in the change in the number of jobs, but also in the change in job requirements. The literature suggests that the development of AI technologies can change the tasks and skill requirements of labor jobs. Autor (2003) constructed a model that distinguishes between programmatic and non-programmatic tasks and argues that AI technologies can only replace low-skilled programmatic tasks [8]. However, AI technologies based on big data, machine learning, and distributed computing can perform more unconventional tasks, and even some high-skilled non-programmed tasks. Therefore, the progress of AI technology makes the change of job requirements more significant. Meanwhile, the accelerated upgrading of industrial structure will lead to a continuous increase in the demand for highly educated labor in enterprises, while technological advances will drive the transformation of traditional industries from labor-intensive to knowledge-intensive, which will significantly increase the demand for highly qualified personnel [17]. Existing studies also suggest that advances in AI technologies will lead to changes in the skill structure of the labor market; for example, Dahlin (2022) states that AI technologies will lead to the need for more social, creative, and cognitive skills in some occupations and less physical, manual, and repetitive skills. The increase in the level of information and intelligence will replace middle-skilled jobs, and the scale of labor employment in both high-skilled and low-skilled groups will expand [18]. On the one hand, the input of AI technology will impact low-skilled labor employment, but the application of new products or services will change the skill demand for labor by firms [19]. As technological advances deepen, the impact of AI on the medium-skilled labor force gradually diminishes [20], and the demand for high-skilled personnel in its native industry clusters increases [21]. On the other hand, industrial robot inputs show a substitution effect on the manufacturing industry in general, and the invested robots produce a direct competition with labor, and robot applications will also make the demand for medium-skilled labor in enterprises will continue to decrease and increase the demand for high-skilled and highly educated personnel.

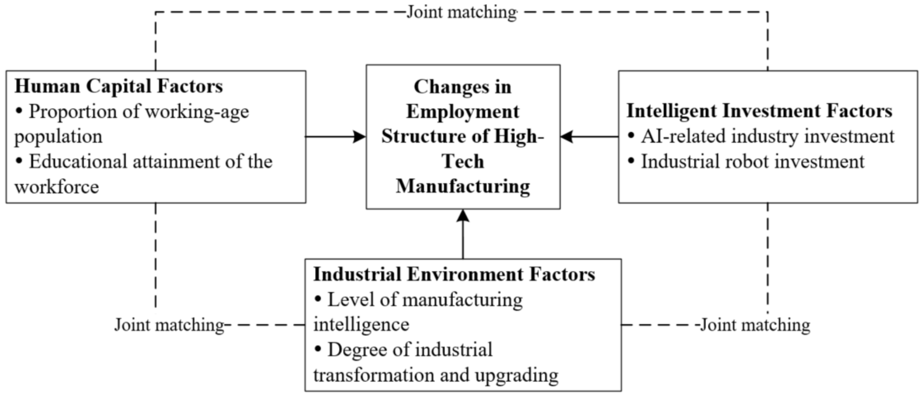

Figure 1. Theoretical Model Framework

3. Quantitative Data Analysis Process

3.1. Applicability of Qualitative Comparative Analysis Method (QCA)

Qualitative Comparative Analysis (QCA) was proposed by Larkin (2008). From the perspective of holism, it considers management composed of antecedents, focusing on the configuration of conditions and the complex causal relationship between results, and is a new paradigm for social science research. Traditional econometric research models adopt a single causal assumption, believing that various factors are independent of each other, and viewing the external environment and internal attributes of an organization as linear and one-way causal relationships. From the perspective of configuration research, it is believed that different combinations of antecedents can form multiple concurrent causal relationships, which can generate multiple equivalent causal chains. Since the QCA method believes that the configuration of antecedents has complete equivalence to the explained results without conflict, it is very appropriate to explore the complex mechanism of multiple conditions affecting the changes in the employment structure of the manufacturing industry from a holistic perspective.

QCA configuration analysis methods mainly include csQCA, mvQCA, and fsQCA, respectively corresponding to qualitative comparative analysis of clear sets, multivalued sets, and fuzzy sets. Because fuzzy sets have both qualitative and quantitative attributes, combining the kind and degree of membership of the set, they have the advantages of many fixed distance variables and the ability to accurately distinguish between them. Compared to clear sets and multivalued sets, fuzzy sets implement a more accurate and rigorous consistency assessment of set theory, and the analysis results are more compact in empirical terms, which can reduce the generation of contradictory configurations. Therefore, this paper adopts the fuzzy set fsQCA method for data processing.

3.2. Samples and Data

This article limits the scope of data collection to domestic provincial panel data, and ultimately selects provincial panel data from 2018 to 2020 for empirical research. The data in this article are sourced from the “China Statistical Yearbook”, “China Industrial Enterprise Database”, “China Labor Statistics Yearbook”, “China Science and Technology Statistics Yearbook”, and the International Federation of Robotics (IFR) over the years. See the “Measurement and Calibration” section for other relevant data sources.

3.3. Measurement and Calibration

Calibration is the process of assigning membership values to a case set, converting distance or scale data to fuzzy sets using standard calibration procedures in software. Consistent with existing calibration principles [22], this article uses the direct calibration method to calibrate the antecedent condition variable and result variable data into fuzzy set membership scores, using 95%, 50%, and 5% quantile values as thresholds for complete membership, intersection, and complete non membership, respectively. Table 1 shows calibration data for antecedent conditions and result.

Table 1. Calibration Process and Results of Conditional Variables

Condition variables and result variables	Calibration		
	Full subordination	Cross point	Not affiliated at all
Changes in the employment structure of the workforce	0.794	0.320	0.178
AI-related industry investment	422.152	211.040	66.741

Industrial robot investment	2 717 591	626 837	11 370
Industrial intelligence level	63.300	53.700	45.860
Industrial transformation and upgrading	0.687	0.517	0.471
Population structure of working-age labor force	77.250	71.370	66.660
Educational attainment of the workforce	0.427	0.165	0.112

3.3.1. Result Variables and Measurements

The outcome variable is the change in the employment structure of the workforce, measured by the proportion of high-tech manufacturing labor in the total number of manufacturing workers. Previous studies have measured the labor employment structure from a supply perspective, using highly educated backgrounds or highly skilled positions. However, this statistical method has a relatively low supply elasticity and a relatively slow response to market demand, which fails to reflect the real demand situation in the employment market. This article analyzes the employment structure of the workforce through occupational categories, using the year-end average number of workers in the classification of high-tech industries to measure the proportion of highly skilled labor. The reasons are as follows: There is no clear classification of high-tech manufacturing industries, and using the "Classification of High Technology Industries (Manufacturing)" can obtain a relatively consistent result with the employment structure of high-tech manufacturing industries from panel data. Compared to other manufacturing industries, the expansion of high-tech manufacturing industry is more conducive to high-quality development of the industry. The high-tech manufacturing industry is a manufacturing industry with relatively high investment in scientific research and experimental development (R&D). These industries have created more knowledge stocks and conducted creative and systematic work to design new applications of existing knowledge. Therefore, the high-tech manufacturing industry has attracted more highly skilled talents.

First of all, this research uses the definition and classification of industrial high-tech categories in the Classification of High Technology Industries (Manufacturing Industry) published by the National Bureau of Statistics to classify employees in six major industries, including pharmaceutical manufacturing, aviation, spacecraft, and equipment manufacturing, electronic and communication equipment manufacturing, computer and office equipment manufacturing, medical equipment and instrumentation manufacturing, and information chemicals manufacturing, as high-tech manufacturing labor categories. Secondly, based on the industries included in the above six major industry categories (including large, medium, and small categories), the average year-end employment numbers of each industry over the years were found from the "China Industrial Statistics Yearbook" published by the Industrial Transport Statistics Department of the National Bureau of Statistics, and the data were consolidated for the same type. Finally, summarize the labor force counted at the end of the year by industry category to obtain the average labor force in high-tech manufacturing at the end of the year. This paper calculates the ratio of high-tech manufacturing labor force size to non-high-tech manufacturing labor force size for each year from 2018 to 2020, and uses it as a basis for evaluating changes in the employment structure of manufacturing labor force.

3.3.2. Conditional Variables and Measurements

Human Capital Factors. The supply of labor resources is divided into the quantity and quality of talent supply. In existing research, most of the regional human capital levels are calculated based on the composition of education expenditure in each province, such as the proportion of regional financial education expenditure to the general financial budget. However, such methods are calculated and analyzed from the perspective of financial investment, and cannot reflect the actual supply level of human capital in the entire labor market [16]. Therefore, this article combines the conclusions of qualitative interviews and draws on the practices of existing research to measure the level of labor resources in various provinces using two dimensions: the proportion of the working-age population aged 15-64 and the average length of education.

Industrial environmental factors. Mainly include the level of industrial intelligence and industrial transformation and upgrading. Based on the conclusions of qualitative interviews and the practices of existing research, this article uses the indicator data of the Ministry of Industry and Information Technology's integration platform to measure the degree of regional industrial intelligence, and assigns a membership value after standardizing the regional data for 2018-2020. At the same time, regional industrial upgrading and the development of third-party service industries will bring about labor mobility, which has a significant impact on the labor employment structure. This article uses existing research for reference to measure the upgrading of industrial structure based on the total industrial added value/GDP of a region.

Intelligent Investment Factors. Mainly include the development scale of artificial intelligence and investment in industrial robots. Due to the relevance of the artificial intelligence industry to other industries, industries such as software and information technology services are classified as artificial intelligence industries. Based on the conclusions of qualitative interviews and the practice of Boland (2017) [23], this article selects the total social asset investment in information transmission, computer services, and software industries from the China Statistical Yearbook to represent the development scale of artificial intelligence technology. In addition, investment in industrial robots is a key variable to measure the degree of automation triggered by technological progress. The development of artificial intelligence will transform the workplace through automation and intelligence, thereby changing the employment structure of the workforce. Based on existing research, this article combines the input data of industrial robots in various industries of the International Federation of Robotics (IFR) and the input data of provinces in the China Industrial

Yearbook to allocate the input of industrial robots over the years to various provinces according to the scale of each industry, and finally obtains the input level of industrial robots in different provinces.

4. Quantitative Data Analysis and Empirical Results

4.1. Single Condition Necessity Analysis

This article follows existing research standards and conducts a necessity test on each conditional variable in the study to analyze whether a single factor is a necessary condition for the outcome variable, and to identify the conditional configuration that best explains the target case. The important measure of whether it is a necessary condition is the consistency level of a single condition. A necessary condition refers to the existence of the antecedent conditions that lead to the occurrence of a result. If the consistency level of a single condition is higher than 0.9, this condition constitutes a necessary condition for the result. This article obtains the data results of the necessary conditions for changes in the employment structure of high/non-skilled labor through the fsQCA3.0 software, as shown in Table 2. From Table 2, the consistency of all conditional variables is less than 0.9, so there is no necessary condition for the change in the proportion of high-tech manufacturing labor in this model.

Table 2. Analysis of the necessary conditions for changing the labor force structure

Conditional variable	Increase in the proportion of high-tech manufacturing labor		Non-increase in the proportion of high-tech manufacturing labor	
	Consistency	Coverage	Consistency	Coverage
AI-related industry investment	0.694	0.689	0.522	0.618
Non- AI-related industry investment	0.615	0.519	0.737	0.742
Industrial robot investment	0.781	0.790	0.448	0.541
Non-industrial robot investment	0.546	0.453	0.826	0.818
Manufacturing intelligence	0.824	0.780	0.466	0.526
Non-Manufacturing intelligence	0.499	0.439	0.805	0.845
Upgrade of industrial structure	0.740	0.713	0.556	0.640
Non-industrial structure upgrading	0.626	0.541	0.751	0.775
Working-age proportion	0.627	0.595	0.606	0.687
Non-Working-age proportion	0.670	0.588	0.642	0.672
Population supply quality	0.681	0.716	0.526	0.659
Non-population supply quality	0.676	0.544	0.773	0.743

4.2. Conditional Configuration Adequacy Analysis

Configuration analysis is different from necessary condition analysis in that it analyzes the adequacy between conditional variables and outcome variables, revealing the results caused by different configurations composed of multiple conditions. When using consistency to measure the adequacy of a configuration, the consistency level of conditional configuration adequacy is typically greater than 0.75 [24]. In actual research, determining the frequency threshold requires considering the size of the sample size. The consistency level threshold of a case also needs to be determined based on the truth table and the specific situation of the case. For small sample data, the threshold is generally set to 1.

In the practice of research methods, the 1 or 0 configuration cases in the results should be covered and roughly balanced; The frequency threshold set should cover at least 75% of the sample cases; To reduce potential conflicting configurations and avoid simultaneous subset relationships, the PRI consistency is generally not less than 0.75. Based on the judgment of the number of case samples and the “breakpoint” of the consistency level, due to the breakpoint appearing in the data of this study when the

RAW consistency is 0.92, this article follows the criteria of existing research, setting the case frequency threshold to 1, the PRI consistency threshold to 0.67, and the RAW consistency threshold to 0.92. At the same time, this article analyzes “non set” and explores the situation of “causal asymmetry”. When processing “non” sets, the case frequency threshold is set to 1, the PRI consistency is 0.76, and the RAW consistency is 0.94, consistent with the basic criteria of the research method.

Due to the lack of clear and consistent conclusions on how antecedents affect changes in the employment structure of the workforce in existing research, it is difficult to make a clear counterfactual analysis in this article. Therefore, in the step of generating an intermediate solution, the question of “presence or absence” is chosen when faced with which of the five conditions will lead to an increase in the proportion of highly skilled labor. In the fsQCA analysis, in order to correctly handle logical residuals, it is necessary to avoid using complex and simplified solutions. Intermediate solutions should be selectively used based on practical and theoretical knowledge, supplemented by simplified solutions for interpretation. Table 3 shows the results of conditional configuration paths. The results presented in this article are consistent with previous studies, where a solid circle indicates the existence of a condition, a circle with a cross indicates the absence of the result, and a blank indicates a fuzzy state. The condition may or may not exist. The large circle represents the core condition, and the small circle represents the auxiliary condition.

From a single perspective, industrial robot investment and industrial intelligence exist as core conditions in the “and set” configuration, indicating that the two are significantly related to the increase in the proportion of highly skilled labor. Moreover, the lack of both is the main reason for the appearance of “non centralized” configuration paths. In addition, a higher AI development scale and labor education background are also key conditions for the increase in the proportion of highly skilled labor. From the perspective of the relationship between configurations and the configuration path of “increasing the proportion of highly skilled and non-highly skilled labor”, the investment in industrial robots has a significant impact bias, and the stock of human capital and the upgrading of industrial structure have an important impact on the reduction of the proportion of highly skilled labor. For the above relationship mechanism, in-depth explanation and case analysis will be conducted in the discussion section.

Table 3. Configuration analysis of the proportion of highly skilled labor

Conditional variable	Increase in the proportion of highly skilled labor			Increase in the proportion of non-highly skilled labor				
	Key pilot type		Comprehensive development type	To be developed type		Investment driven type	Stock supply type	
	1	2	3	4	5	6	7	8
A		•				●	•	⊗
B	●	●	●	⊗	⊗	⊗		•
C	●	●	●	⊗	⊗		⊗	⊗
D		●	●		⊗	⊗	●	•
E	⊗					•	•	•
F	●		•	⊗		⊗	⊗	•
Consistency	0.965	0.942	0.981	0.912	0.909	0.986	0.959	0.998
Original coverage	0.346	0.466	0.492	0.594	0.589	0.257	0.193	0.162
Unique coverage	0.040	0.092	0.068	0.068	0.063	0.024	0.017	0.016
Consistency of all solutions		0.935		0.893				
Coverage of all solutions		0.624		0.731				

Note: A for AI-related industry investment; B for Industrial robot investment; C for level of manufacturing intelligence; D for degree of industrial transformation and upgrading; E for proportion of working-age population; F for educational attainment of the workforce

5. Discussion

Based on the core and auxiliary conditions contained in the eight conditional configurations, this article summarizes the paths of AI technological progress affecting the changes in the employment structure of the manufacturing labor force into five types of models, namely, comprehensive development, key leadership (including capital leadership and education leadership), stock supply, investment driven, and pending development. For “comprehensive development type”, see Configuration 3 path; “Key pilot type” is shown in the path of Configuration 1 and Configuration 2. The other three modes are shown in configuration 4-8 in Table 3. The following will discuss the two types of causal relationships separately.

5.1. Conjunctural Sets Discussion

Firstly, in-depth research is conducted on configurations 1 to 3. Comparing the three types of configuration paths, investment in industrial robots and the level of industrial intelligence are key factors driving the increase in the proportion of highly skilled labor, which reflects the job creation effect of artificial intelligence, that is, the application of artificial intelligence increases the demand for relevant positions in high-tech sectors of the manufacturing industry. Among them, Configuration 1 is an education oriented model, which means strengthening education investment under resource constraints. The characteristic is that the regional manufacturing industry is not large and needs to rely on education improvement to drive development; Configuration 2 is a capital led model, with capital investment as the main antecedent, characterized by a large volume of regional manufacturing industry and a high degree of capital investment; Configuration 3 is a comprehensive development model, with balanced scores for various antecedents and synergy. It is characterized by a moderate scale and size of the regional manufacturing industry, with all aspects of conditions available. With the continuous penetration of artificial intelligence technology into the manufacturing industry, these three types of development models can increase the proportion of high-tech manufacturing labor.

From the “comprehensive development model”, increasing investment in industrial robots and industrial transformation and upgrading will increase the proportion of high-tech manufacturing labor and optimize the employment structure of labor when the level of industrial intelligence and education of labor in a region are high. The characteristic of this path is that although the levels of various dimensions affecting the employment structure have not reached the highest level, they are well balanced, promoting the increase in the proportion of highly skilled labor with a healthy development structure. The biased theory of technological progress proposes that various types of technological progress indicators have different effects on the labor structure, while the development scale of artificial intelligence, the use of industrial robots, and industrial intelligence will all impact the labor skill demand structure, causing changes in the proportion of highly skilled labor. Further, when technological progress changes the demand structure of the above-mentioned labor force, if there are many workforces of suitable age and highly educated workers in the employment market, there will be a trend towards an increase in the proportion of highly skilled labor in the employment structure. Therefore, when the education background of the labor force in a region is good and the level of industrial intelligence is high, increasing investment in industrial robots and improving the level of industrial transformation and upgrading can optimize the employment structure of high-tech manufacturing industries. Typical provinces adopting this development model include Beijing, Shanghai, and Zhejiang. For example, the Beijing Municipal Government has been vigorously promoting the development of intelligent manufacturing, forming an industrial structure dominated by high-tech manufacturing by strengthening technology research and development and building intelligent manufacturing bases. In addition, Beijing has also strengthened investment in higher education, vocational education, skill training, and other aspects, improving the quality of talent cultivation, providing talent protection for the development of high-tech manufacturing industry, and attracting a large number of outstanding talents to serve the high-tech manufacturing industry.

It can be seen from the “key pilot development model” that under this investment model, there are two paths for the change in the proportion of high-tech manufacturing labor. The first is a capital led path. In regions with high levels of industrial intelligence and industrial structure transformation, increasing capital investment can increase the proportion of highly skilled labor and optimize the employment structure of labor. Further, in regions with high levels of industrial intelligence and industrial structure upgrading, improving the scale of AI investment and the deepening of manufacturing capital is a key condition for increasing the proportion of highly skilled labor. Typical provinces using this model include Guangdong Province, Sichuan Province, and Shandong Province. For example, Guangdong Province is the economic center of southern China, with a very large GDP and manufacturing scale. Manufacturing industry is one of the pillar industries in Guangdong Province, which mainly develops electronic information, household appliances, automobile manufacturing, etc., and has a great demand for industrial robots and artificial intelligence applications. Therefore, the amount and scale of investment in artificial intelligence are larger, and it is easier to rapidly expand the development scale of its own high-tech manufacturing industry. In addition, unlike Beijing, which pays more attention to independent innovation and independent research and development, Guangdong Province has a high degree of openness to the outside world and has certain advantages in introducing foreign robots and technologies and exploring intelligent manufacturing, resulting in a higher level of industrial intelligence. The improvement of industrial intelligence has also prompted industrial robots to replace more repetitive and low-skilled jobs, driving the increase in the proportion of high-tech manufacturing labor.

The second is the education led path. In regions with high numbers of industrial intelligence and industrial robots, the number of workforces of suitable age is small, but the proportion of workforces with high education backgrounds is high. High labor quality has become a key condition for the increase in the proportion of high-tech manufacturing labor. As the manufacturing industry continues to increase the use of industrial robots, promoting the transformation of intelligent manufacturing, the demand for skilled and knowledge-based talents has increased significantly. Areas led by education should first increase investment in education. With a workforce with a higher education background, the level of human resources can well meet the needs of the region to develop artificial intelligence. Therefore, although the number of school-age labor is relatively scarce, areas with higher education levels of labor have certain advantages in developing artificial intelligence. Typical provinces along this path include Chongqing City, Jiangsu Province, and Hubei Province. For example, Chongqing has a rich manufacturing base and a high proportion of manufacturing industry, so it has a high advantage in increasing investment in industrial robots and promoting industrial intelligence. Moreover, Chongqing can radiate the entire western region, and it has unique measures and efforts in promoting the modernization of vocational education, improving the level of vocational education teachers, and promoting the cultivation of skilled talents. The vocational education track has gathered a large number of innovative and entrepreneurial talents.

5.2. Non-conjunctural Sets Discussion

The configurations appearing in “non-conjunctural sets” can be summarized into three categories. In the configuration path, one is the type to be developed, that is, the development scale of artificial intelligence and the level of industrial intelligence are both low, which is a key condition leading to a relatively low proportion of high-tech manufacturing labor in the region. This model is seen in provinces where the development of artificial intelligence is relatively backward, and the scale of high-tech manufacturing in the region is limited. The second is investment driven, which means that the development of artificial intelligence has a large scale, but the low number of industrial robots will also lead to a relatively low proportion of high-tech manufacturing labor. This model is seen in regions that attach great importance to the development of artificial intelligence and have made a large amount of investment in artificial intelligence, but have relatively weak industrial intelligence foundations. The third is the stock supply type, which means that the degree of industrial intelligence is relatively low, but the proportion of labor of suitable age is relatively high, which is a key condition leading to a relatively low proportion of high-tech manufacturing labor in the region. This model is found in areas where there is a large supply of labor resources, but industrial intelligence is not developed. When the regional labor supply is large, the labor-intensive service sector absorbs a large amount of labor, resulting in the flow of labor from the highly productive manufacturing sector to the low-productivity service sector. This process of labor migration from manufacturing to service industries will also lead to a decline in the number of workers employed in high-tech manufacturing industries.

6. Implications

6.1. Conclusions

The study shows that the change of labor force structure in the manufacturing industry is the result of multiple factors, and no single factor can constitute a sufficient or necessary condition. There are three main paths that drive the increase of labor force in high-tech manufacturing, including “comprehensive development”, “capital-led” and “education-led”; the paths that cause the decrease of labor force in high-tech manufacturing include “pending development”, “stock supply” and “investment driven”. If the intelligence level of regional industries is low but the proportion of working-age population is high, the labor force share of high-tech manufacturing will be decreasing; if the intelligence level of regional industries and the education level of labor force are high, the labor force share of high-tech manufacturing will increase if the investment in industrial robots is increased. This finding deepens the judgment of the theory related to biased technological progress and expands the dimension of theoretical explanation for the change of employment structure caused by technological progress.

6.2. Theoretical Implications

Firstly, this study provides a new perspective on the analysis of the employment structure configuration of high-tech manufacturing industries. Although existing studies have analyzed the impact of various factors on the employment structure based on the theory of technological progress, such as the application of information technology and capital deepening, they focus more on the variability of each factor rather than the combined effect [25]. In this paper, we analyze the multiple causal relationships between antecedent conditions through the fsQCA method, and confirm that there are multiple paths that cause changes in the employment structure of high-tech manufacturing industries, and there are multiple equivalent causal chains of the same path. The findings promote the transformation from a single perspective to a multidimensional perspective in analyzing the impact of new technologies on the change of employment structure in high-tech manufacturing industries, and provide a research basis for the subsequent deepening of the analysis of labor force employment structure configuration.

Secondly, this study reveals a new mechanism by which technological progress of artificial intelligence affects the change of employment structure in high-tech manufacturing industry. The technological investment in artificial intelligence, together with industrial environment factors and labor resource factors, will generate a configurational relationship and jointly trigger the linkage effect of employment structure change. The findings of this paper echo the existing research findings that industrial robots and increased industrial intelligence are important drivers of the increase in the share of high-skilled labor [5], and that the scale of AI development and regional education level are important variables in adjusting the employment structure. Further, it was found that in regions with higher levels of industrial intelligence, increased investment in education would also increase the share of high-tech manufacturing workforce. Thus, this paper constructs a linkage matching model for the change of employment structure in high-tech manufacturing from the perspective of technological progress from the skill-biased technological progress theory, further explores the linkage configuration of the antecedents in this model, elucidates the variability of the factors that trigger the increase of the share of labor force in high-tech manufacturing, and confirms the effectiveness of the linkage matching model in explaining the change of employment structure.

6.3. Practical Implications

Firstly, enhance the level of industrial intelligence and increase the application of industrial robots. Research shows that the level of regional industrial intelligence is a fundamental factor in promoting the healthy development of high-tech manufacturing industries, and the application of industrial robots has become an important choice for manufacturing enterprises to use artificial intelligence to cope with the labor shortage. High-tech industrial clusters should actively promote the digital transformation and intelligent upgrading of industries, widely adopt advanced information technology and data analysis methods, and enhance the attractiveness of high-tech manufacturing to highly qualified talents. Industrial robots can complete operations with high precision, quality, and efficiency, improve the working environment and reduce production accidents, allowing workers to focus more on highly skilled and creative work. If there are more repetitive, physically heavy and tedious tasks in high-tech manufacturing, then highly qualified talents are reluctant to go to manufacturing, and the diversion effect of emerging service industries on talents will be more obvious.

Secondly, improve employees' digital skills and literacy through education and training. Research shows that the level of human resources in a region can meet the talent demand for artificial intelligence investment, which will promote the healthy development of high-tech manufacturing industry. With the popularization of industrial robots and the improvement of industrial intelligence level, the nature of manufacturing jobs is changing, requiring more highly skilled and innovative talents. To adapt to the application of artificial intelligence technology and equipment in high-tech manufacturing industry, employees need to have digital skills and literacy. For those who have already been impacted by artificial intelligence, retraining on digital skills and literacy is particularly important. Therefore, local human resources departments can provide more workers with training on digital skills and literacy through online learning platforms, face-to-face training courses, workshops, practical projects etc., so that they can better adapt to new work environments and tasks as well as make better use of AI devices and other digital tools. In addition, governments can lead efforts to establish certification systems for digital skills and literacy in industry organizations or educational institutions to assess employees' levels of proficiency in these areas while encouraging them to continuously learn how to collaborate with AI.

Thirdly, promote the integration of manufacturing and service industries and optimize the development environment of high-tech manufacturing. Research shows that the degree of industrial transformation and upgrading has a well-synergistic effect with the level of industrial intelligence and industrial robot input. The integration and development of information service industry, science and technology service industry and manufacturing industry can realize the integration and mutual promotion of old and new dynamic energy; the enhancement of high-tech manufacturing industry scale will strengthen the development foundation and market demand of production service industry, promote the integration and development of high-tech manufacturing industry and production service industry, and promote the expansion of production service industry to specialization and high-tech. Therefore, the management department needs to actively layout and build industrial innovation platforms, pilot production service platforms, test and verification platforms, demonstration application platforms, and create R&D services, scientific and technological consulting and inspection and testing pillar industries. Through the above-mentioned measures of industrial integration development, high-tech talents serving in the productive service industry will be attracted to actively participate in the development of high-tech manufacturing industry, or even directly serve the high-tech manufacturing industry, further importing the talent dividend into the high-tech manufacturing industry.

Finally, strengthen overall planning and form a policy toolbox. Government management departments should strengthen overall planning, consider various factors and the relationship between high-tech manufacturing industry employment structure comprehensively, design multiple strategies and approaches, form a policy toolbox, and take multiple measures to promote the development of high-tech manufacturing industry. Local governments should fully recognize the level of local industrial intelligence, reasonably judge the resource endowment for developing high-tech manufacturing industries locally, and choose suitable resource combination strategies. A more comprehensive and integrated perspective is needed. On one hand, it is necessary to comprehensively consider the quantity and quality of labor resources supply in the local area as well as expected investment in artificial intelligence and input level of industrial robots to clarify their own development positioning; on the other hand, new factors affecting employment structure in high-tech manufacturing industries need to be continuously explored while planning more resource combinations that can increase proportion of skilled workers in this field. For areas belonging to the first three models mentioned above (in an earlier part of text), based on their actual situation they should further improve their weaknesses while enhancing strengths gradually towards becoming comprehensive development types.

7. Limitations and Prospects

There are some limitations in this study. First, the scope of our study is limited to the high-tech manufacturing sector, which may not provide a comprehensive picture of the entire manufacturing sector. Second, we used the fsQCA method for our analysis, and although we were able to explore the complex relationship between multiple conditions, there are also limitations and biases in the study data that may affect the accuracy of the findings. In addition, our study considered the antecedent factors affecting the labor force share of high-tech manufacturing, and there may be omissions in the effects of cost of living, total factor productivity, and other factors. The model needs to be further enriched in the future to explore more paths of antecedent condition grouping.

In order to further deepen the study, future research can be conducted in the following aspects: first, the scope of the study can be expanded to the whole manufacturing industry to analyze the grouping effects of structural changes in manufacturing employment from a more comprehensive perspective. Secondly, other research methods can be applied to the analysis to ensure the accuracy and reliability of the research results. Meanwhile, other conditions driving the increase of the labor force share in high-tech manufacturing can also be explored to comprehensively analyze the mechanisms of labor force structural changes in manufacturing. Finally, the research perspective can be expanded to an international scale to explore the commonalities and differences in the changes of manufacturing employment structure in different countries and regions. These studies will help to understand more comprehensively and deeply the mechanisms and influencing factors of the changes in manufacturing employment structure, and provide strong support for future policy formulation and industrial development.

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