

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON EMPLOYMENT IN GUANGDONG'S MANUFACTURING SECTOR AMID DIGITAL TRANSFORMATION

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Abstract: Against the backdrop of industrial digital transformation, artificial intelligence (AI) technology is profoundly reshaping the employment structure in the manufacturing sector. Based on survey data from 423 manufacturing enterprises in Guangdong, this study employs analysis of variance (ANOVA) and benchmark regression models to systematically analyze the impact of AI applications on changes in employment scale, job demand, and skill requirements. The results indicate that AI generally exerts a significant positive effect on the employment scale in the manufacturing sector; factors such as the proportion of R&D investment in AI, the growth rate of AI investment, and the proportion of AI-related personnel all significantly drive employment growth. There is marked heterogeneity in employment changes across industry types, enterprise sizes, and enterprise nature, with more pronounced adjustments observed in the equipment manufacturing sector, high-tech manufacturing, as well as in medium-to-large enterprises, foreign-invested, and joint-venture enterprises; AI is driving a shift in job demand toward intelligent roles such as AI R&D engineers and industrial data analysts, while simultaneously prompting an upgrade in skill requirements toward composite competencies in data analysis, human-machine collaboration, and innovative problem-solving. The study's conclusions can serve as a reference for human resource structural adjustments and employment policy formulation in Guangdong's manufacturing sector.

Keywords: Digital transformation; Artificial intelligence; Guangdong manufacturing; Employment impact

1 INTRODUCTION

As a national hub for advanced manufacturing and a host for international science and technology innovation centers, Guangdong Province is accelerating the digital and intelligent transformation of its manufacturing sector. The province has established a systematic policy framework centered on the Guangdong Action Plan for AI-Empowered High-Quality Development of Manufacturing (2025–2027), driving comprehensive industrial upgrading through a four-pronged approach of supply, application, support, and factors [1]. The Guangdong-Hong Kong-Macao Greater Bay Area is accelerating the development of an industrial science and technology innovation center with global influence. In the fields of artificial intelligence and robotics, Guangdong has formed an industrial landscape centered on Guangzhou, Shenzhen, Foshan, Dongguan, and Zhuhai, with coordinated development across the Pearl River Delta.

As the manufacturing sector accelerates its transformation toward digitalization and intelligent upgrading, new types of talent have emerged as a new form of productive force driving “Made in China” toward high-end development; however, the structural impact of artificial intelligence on the job market is also becoming increasingly significant [2-4]. Li Junyu et al. found, through an extended job-task model, that the impact of AI exacerbates income disparities across different occupations through three mechanisms: the substitution effect, the productivity-enhancing effect, and the technology gap effect; meanwhile, excessive expansion of education may actually amplify this wage polarization effect [5]. Jiang Wei et al. used a multi-sector general equilibrium model to reveal that AI drives an increase in the share of the service sector and boosts labor productivity through dual structural effects on capital and skills, but it also widens the income gap between low- and high-skilled workers [6]. Ribeiro and Prettnner, based on panel data from 52 countries, found that industrial robots widen income inequality, while AI suppresses wages for high-skilled workers and boosts wages for low-skilled workers, with this effect being stronger in high-income countries [7]. Duan Meng distinguished the heterogeneous impacts of AI and industrial robots by constructing a three-level nested CES production function. Higher levels of AI adoption suppress wages for high-skilled workers, while industrial robots exert a negative impact on wages for low-skilled workers. However, when both technologies are adopted at high levels, their interaction creates a synergistic mechanism that narrows the skill premium [8].

As noted above, current academic research on the impact of AI on the labor market has accumulated a substantial body of theoretical knowledge. However, existing literature primarily focuses on macro-level analyses of income disparities or evaluations of the effects of single technology types [9-11], and there remains a lack of systematic empirical testing regarding the mechanisms linking AI applications to the employment structure in manufacturing under the context of digital transformation—particularly the heterogeneous manifestations across regions with distinct industrial characteristics. As China's leading manufacturing province, Guangdong boasts dense industrial clusters in electronics and information technology, equipment manufacturing, and home appliances and furniture, and is at the forefront of the nation's digital transformation. This not only provides a vast arena for the in-depth application of AI technologies but

also subjects its labor market to more complex structural adjustment pressures. Against this backdrop, to investigate the impact of AI on the scale of employment, job roles, and skill demands in Guangdong's manufacturing sector, this study focuses on manufacturing enterprises in Guangdong. Through questionnaire surveys, it analyzes the multidimensional effects of AI on these aspects, revealing the employment outcomes driven by AI. The findings aim to provide empirical evidence and references for manufacturing enterprises in Guangdong to adapt their human resource management strategies and for the government to implement targeted policies.

2 RESEARCH SUBJECTS AND METHODS

This study employs a questionnaire survey method to investigate the impact of AI on employment in Guangdong's manufacturing sector against the backdrop of digital transformation. The survey was conducted from June to November 2025, with 500 questionnaires distributed and 423 valid responses collected, yielding a response rate of 84.6%. The survey sample covered 11 prefecture-level cities in Guangdong Province and spanned four major industries: light industry (consumer goods manufacturing, such as food and textiles), heavy industry (means of production manufacturing, such as steel and machinery), equipment manufacturing (such as machine tools and automobiles), and high-tech manufacturing (such as electronics and information technology, and biopharmaceuticals). The respective shares of these four industries were 24.54%, 23.94%, 25.39%, and 26.12%; Enterprise size distribution was as follows: fewer than 50 employees (30.62%), 50–300 employees (26.49%), 301–1,000 employees (25.15%), and more than 1,000 employees (17.74%); Enterprise ownership includes private enterprises (47.39%), state-owned enterprises (21.14%), foreign-invested enterprises (20.17%), and joint ventures (11.3%).

To investigate differences in employment patterns among manufacturing enterprises with varying characteristics in the context of artificial intelligence, this study employs analysis of variance (ANOVA). Using enterprise size, industry type, and enterprise nature as grouping variables, the study tests whether there are significant differences in changes in employment scale, job demand, and skill requirements across enterprises with different characteristics. All statistical analyses were conducted using SPSS 26.0 software, with a significance level set at 0.05.

To further investigate the impact of artificial intelligence on employment in Guangdong's manufacturing sector, this study employs a benchmark regression model. With changes in manufacturing employment in Guangdong Province as the dependent variable and the intensity of AI application as the core explanatory variable, the constructed regression model is as follows:

$$ES_i = \alpha_0 + \alpha_1 RD_i + \alpha_2 IG_i + \alpha_3 SP_i + \alpha_4 JQ_i + \alpha_n \text{Control}_i + \varepsilon_i \quad (1)$$

$$PD_i = \alpha_0 + \alpha_1 RD_i + \alpha_2 IG_i + \alpha_3 SP_i + \alpha_4 JQ_i + \alpha_n \text{Control}_i + \varepsilon_i \quad (2)$$

$$SD_i = \alpha_0 + \alpha_1 RD_i + \alpha_2 IG_i + \alpha_3 SP_i + \alpha_4 JQ_i + \alpha_n \text{Control}_i + \varepsilon_i \quad (3)$$

Where: ES_i represents changes in employment scale; PD_i represents changes in skill demand; SD_i represents changes in skill demand; RD_i represents the proportion of R&D investment in AI; IG_i represents the growth rate of AI investment; SP_i represents the proportion of personnel in AI-related positions; JQ_i represents the quality evaluation of AI-related positions; Control_i is a set of control variables, including industry type, enterprise scale, and enterprise nature; ε_i denotes the random disturbance term.

3 DIFFERENCES IN MANUFACTURING FIRM CHARACTERISTICS AND EMPLOYMENT UNDER THE CONTEXT OF ARTIFICIAL INTELLIGENCE

3.1 Differences in Manufacturing Enterprise Characteristics and Changes in Employment Scale in the Context of Artificial Intelligence

Table 1 Results of the Analysis of Differences in Employment Scale Changes Across Different Enterprise Characteristics

Variable	Type	Total Number of Employees	Proportion of Highly Skilled Employees	Proportion of Medium-Skilled Employees	Proportion of low-skilled employees
Industry Type	Light industry	2.45 ± 1.07	3.34 ± 1.17	2.97 ± 1.12	3.60 ± 1.14
	Heavy Industry	2.52 ± 1.10	3.36 ± 1.17	3.10 ± 1.19	3.68 ± 1.15
	Equipment Manufacturing	2.74 ± 1.25	3.51 ± 1.15	3.12 ± 1.14	3.75 ± 1.15
	High-tech manufacturing	2.73 ± 1.20	3.54 ± 1.09	3.07 ± 1.13	3.77 ± 1.16
	F	3.300	1.780	0.740	0.850
	P	0.020*	0.150	0.528	0.467
Company size	Fewer than 50 employees	2.36 ± 1.16	3.37 ± 1.21	3.01 ± 1.09	3.78 ± 1.14

	50–300 people	2.58 ± 1.04	3.39 ± 1.12	3.00 ± 1.14	3.67 ± 1.14
	301–1,000 people	2.82 ± 1.16	3.45 ± 1.13	3.14 ± 1.18	3.83 ± 1.09
	1,000 or more	2.78 ± 1.28	3.60 ± 1.08	3.15 ± 1.19	3.44 ± 1.21
	F	7.328	1.396	0.985	3.889
	P	0.000**	0.243	0.399	0.009**
Nature of the enterprise	State-owned enterprises	2.43 ± 1.08	3.40 ± 1.15	2.97 ± 1.09	3.67 ± 1.19
	Private enterprises	2.57 ± 1.10	3.38 ± 1.19	2.99 ± 1.17	3.69 ± 1.16
	Foreign-invested enterprises	2.70 ± 1.21	3.61 ± 1.05	3.23 ± 1.13	3.71 ± 1.11
	Joint ventures	2.96 ± 1.43	3.47 ± 1.09	3.26 ± 1.14	3.78 ± 1.12
	F	4.715	1.683	2.965	0.217
	P	0.003**	0.169	0.031*	0.884

Note: ** and * indicate significance at the 1% and 5% levels, respectively. The same applies to Tables 2–3.

As shown in Table 1, regarding industry differences, the P-value for changes in total employee numbers is 0.020, which is less than 0.05, indicating a significant difference. This suggests that there are certain variations in employment scale changes across different industries in the context of artificial intelligence. The mean changes in employee numbers for equipment manufacturing and high-tech manufacturing are relatively high, at 2.74 and 2.73, respectively, indicating that these industries have undergone more pronounced adjustments in labor demand during the process of technological upgrading and intelligent transformation. In contrast, the changes in light industry and heavy industry were relatively minor. Regarding skill structure, the differences across industries in the proportions of high-skilled, medium-skilled, and low-skilled employees did not reach the level of significance, indicating that industry differences have a relatively limited impact on changes in skill structure.

From the perspective of enterprise size, the P-value for changes in total employee numbers was less than 0.01, indicating a highly significant difference, which suggests that there are certain differences in employment scale changes across enterprises of different sizes in the context of artificial intelligence. Medium-sized enterprises (301–1,000 employees) had the highest average change in employee headcount at 2.82, indicating that medium-sized enterprises are more prone to adjustments in employment scale during the intelligent transformation process. This is because medium-sized enterprises are in a critical ramp-up phase of digital transformation, where business expansion combined with technological investment has created a concentrated demand for operational and technical talent. In terms of skill structure, there are also significant differences in the changes in the proportion of low-skilled employees across enterprises of different sizes. The proportion of low-skilled employees is notably higher in micro-enterprises (fewer than 50 employees) and medium-sized enterprises (301–1,000 employees), with average values of 3.78 and 3.83, respectively, while changes in this proportion are relatively moderate for other enterprises. This divergent pattern reveals the differentiated mechanisms by which AI applications reshape the labor structures of enterprises of different sizes.

From the perspective of enterprise nature, the P-value for changes in total employee numbers is 0.003, which is less than 0.01, indicating a highly significant difference. This suggests that changes in employment scale also vary to some extent among enterprises of different natures in the context of AI. Joint ventures exhibited the highest mean change in employee headcount, indicating that they undergo more pronounced adjustments to their employment structure during technological upgrades. Furthermore, significant differences were observed in the changes in the proportion of medium-skilled employees across different enterprise types, with a P-value of 0.031 (less than 0.05). with the mean changes in the proportion of medium-skilled employees reaching 3.23 and 3.26 for foreign-invested and joint-venture enterprises, respectively. This disparity stems from the surging demand for composite medium-skilled talent—individuals proficient in both production processes and digital operations—as foreign-invested and joint-venture enterprises introduce technology and adapt it to local conditions. In contrast, state-owned enterprises are constrained by institutional stability and staffing quotas, while private enterprises, due to relatively weak capital and technological accumulation, have been slower to respond to structural adjustments in medium-skilled talent.

3.2 Differences in Manufacturing Enterprise Characteristics and Job Demand Changes in the Context of Artificial Intelligence

Table 2 Results of Differences in Job Demand Changes Across Different Enterprise Characteristics

Variable	Type	AI R&D Engineer	Industrial Data Analyst	Smart Equipment Maintenance Technician	Traditional Production Line Operator	Quality Inspector	Mid-to-lower-level managers	Supply Chain/Logistics Staff	Customer Service and Sales Staff
Industry Type	Light Industry	1.92 ± 0.88	2.08 ± 0.99	2.09 ± 0.97	1.99 ± 0.86	2.07 ± 0.91	2.11 ± 0.99	2.16 ± 1.13	2.00 ± 0.96
	Heavy industry	2.09 ± 0.92	2.03 ± 0.94	2.22 ± 0.99	1.99 ± 0.83	1.97 ± 0.89	2.16 ± 1.00	1.97 ± 0.95	2.04 ± 0.92
	Equipment Manufacturing	2.26 ± 1.15	2.30 ± 1.10	2.20 ± 1.19	2.17 ± 1.13	2.27 ± 1.09	2.27 ± 1.15	2.25 ± 1.12	2.24 ± 1.03
	High-tech manufacturing	2.27 ± 1.14	2.27 ± 1.16	2.27 ± 1.11	2.20 ± 1.23	2.25 ± 1.20	2.38 ± 1.20	2.24 ± 1.14	2.19 ± 1.10
	F	5.158	3.309	0.996	2.574	3.890	2.418	2.921	2.680
	P	0.002**	0.020*	0.394	0.053	0.009**	0.065	0.033*	0.046
Company size	Fewer than 50 employees	2.10 ± 0.95	2.07 ± 0.98	2.02 ± 0.87	1.95 ± 0.85	1.97 ± 0.87	2.22 ± 1.00	2.04 ± 1.02	2.04 ± 0.91
	50–300 people	1.97 ± 0.89	1.98 ± 0.96	2.07 ± 0.98	1.91 ± 0.91	2.11 ± 0.95	2.10 ± 0.98	2.01 ± 1.00	1.93 ± 0.92
	301–1,000 people	2.29 ± 1.17	2.43 ± 1.15	2.46 ± 1.24	2.36 ± 1.20	2.29 ± 1.21	2.37 ± 1.22	2.42 ± 1.17	2.26 ± 1.13
	1,000 or more	2.23 ± 1.18	2.27 ± 1.11	2.31 ± 1.16	2.24 ± 1.15	2.30 ± 1.13	2.28 ± 1.20	2.23 ± 1.18	2.34 ± 1.09
	F	3.962	7.944	8.281	9.734	5.039	2.295	6.445	6.734
	P	0.008**	0.000**	0.000**	0.000**	0.002**	0.076	0.000**	0.000**
Nature of the enterprise	State-owned enterprise	2.05 ± 0.94	2.03 ± 0.99	2.06 ± 0.93	2.01 ± 0.97	1.96 ± 0.90	2.05 ± 1.01	2.13 ± 1.00	1.98 ± 0.91
	Private enterprises	2.03 ± 0.92	2.08 ± 0.96	2.06 ± 0.96	1.94 ± 0.90	2.05 ± 0.94	2.16 ± 1.01	2.06 ± 1.04	1.97 ± 0.89
	Foreign-invested enterprises	2.28 ± 1.17	2.35 ± 1.16	2.32 ± 1.19	2.31 ± 1.12	2.34 ± 1.19	2.37 ± 1.17	2.20 ± 1.10	2.27 ± 1.09
	Joint venture	2.51 ± 1.33	2.49 ± 1.26	2.80 ± 1.30	2.51 ± 1.34	2.52 ± 1.27	2.63 ± 1.31	2.56 ± 1.36	2.75 ± 1.25
	F	7.040	6.536	14.073	10.880	9.051	7.296	5.468	18.256
	P	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.001**	0.000**

As shown in Table 2, in terms of industry differences, except for the P-value of 0.394 for smart device maintenance technicians and 0.065 for mid-to-lower-level managers, the P-values for changes in demand across the remaining six job categories are all less than 0.05, indicating significant or highly significant differences. This suggests that changes in job demand across different industries under the backdrop of artificial intelligence are clearly diverging. The mean demand for emerging technology positions in the equipment manufacturing and high-tech manufacturing sectors (AI R&D engineers, industrial data analysts) is relatively high, at 2.26 and 2.30, respectively, indicating that technology-intensive industries have a stronger demand for AI-related positions; conversely, the mean demand for traditional positions in light and heavy industries (traditional production line operators, quality inspectors) is relatively low, reflecting a relatively gradual adjustment in the job structure of traditional industries. Among these, the P-values for quality inspectors (0.009) and AI R&D engineers (0.002) showed the most significant industry differences, highlighting the core influence of an industry's technological attributes on job demand.

From the perspective of enterprise size, with the exception of middle and lower-level managers (P-value: 0.076), the P-values for changes in demand across the remaining seven job categories are all less than 0.01, indicating extremely significant differences. This suggests that changes in job demand across enterprises of different sizes are comprehensive and pronounced in the context of artificial intelligence. Most job demand averages were highest among medium-sized enterprises (301–1,000 employees). Specifically, the averages for Industrial Data Analysts (2.43), Smart Equipment Maintenance Technicians (2.46), Traditional Production Line Operators (2.36), and Supply Chain and Logistics Personnel (2.42) were the highest across all enterprise sizes. This indicates that medium-sized enterprises are in a critical phase of digital transformation, with demand surging simultaneously for emerging technology roles, optimized traditional roles, and supporting service positions. The average demand for all types of positions in micro and small enterprises is generally low. In particular, the demand for AI R&D engineers (1.97) and industrial data analysts (1.98) in small enterprises is the lowest, reflecting that micro and small enterprises are constrained by limited resources and lag behind in adjusting their job structures.

From the perspective of enterprise nature, the p-values for changes in demand across all eight job categories were less than 0.01, indicating highly significant differences. This suggests that job demand trends are diverging across enterprises of different types in the context of artificial intelligence. Joint ventures had the highest average demand

across all job categories. Among them, the average demand for smart device maintenance technicians was 2.80, for customer service and sales personnel was 2.75, and for mid-to-lower-level managers was 2.63—all three showing a clear lead. This indicates that joint ventures are most active in optimizing and adjusting positions across the entire value chain during the process of technological integration and business upgrading; Foreign-invested enterprises' demand for emerging technology positions (AI R&D engineers at 2.28 and industrial data analysts at 2.35) ranked second only to joint ventures; The average demand for various positions in state-owned and private enterprises is generally lower. In particular, the demand for traditional production line operators in private enterprises (1.94) and customer service and sales personnel (1.97) is the lowest. This disparity stems from the superior technological advantages, transformation momentum, and resource endowments of joint ventures and foreign-invested enterprises, whereas state-owned enterprises are constrained by institutional factors and private enterprises face limitations in funding and technology, resulting in relatively slower adjustments to their job structures.

3.3 Differences in Manufacturing Enterprise Characteristics and Skill Demand Changes in the Context of Artificial Intelligence

Table 3 Results of Differences in Skill Demand Changes Across Different Enterprise Characteristics

Variable	Type	Technical Skills	Data analysis skills	Ability to operate AI systems	Innovative problem-solving skills	Human-machine collaboration skills	Adaptability to learning	Ability to integrate interdisciplinary knowledge
Enterprise Company	Fewer than 50 employees	3.85 ± 1.07	3.73 ± 1.16	3.80 ± 1.13	3.73 ± 1.07	3.62 ± 1.14	3.73 ± 1.13	3.75 ± 1.08
	50–300 people	3.87 ± 1.12	3.61 ± 1.17	3.81 ± 1.10	3.71 ± 1.16	3.65 ± 1.10	3.77 ± 1.17	3.60 ± 1.15
	301–1,000 people	4.02 ± 0.91	3.95 ± 0.96	3.99 ± 0.94	4.07 ± 0.91	4.08 ± 0.83	4.05 ± 0.86	3.94 ± 0.92
	1,000 or more	4.01 ± 0.90	4.08 ± 0.90	3.91 ± 0.98	3.99 ± 0.89	4.06 ± 0.89	3.94 ± 0.93	3.91 ± 0.97
	F	1.744	7.150	1.530	6.472	12.638	4.470	4.514
	p	0.156	0.000**	0.205	0.000**	0.000**	0.004**	0.004**
Enterprise Nature	State-owned enterprise	3.86 ± 1.10	3.68 ± 1.18	3.80 ± 1.08	3.75 ± 1.11	3.76 ± 1.04	3.81 ± 1.17	3.67 ± 1.06
	Private enterprises	3.85 ± 1.07	3.76 ± 1.12	3.75 ± 1.10	3.79 ± 1.07	3.72 ± 1.10	3.76 ± 1.10	3.74 ± 1.10
	Foreign-invested enterprises	4.07 ± 0.84	4.01 ± 0.91	4.08 ± 0.91	4.10 ± 0.86	3.95 ± 0.93	4.12 ± 0.84	3.87 ± 0.98
	Joint venture	4.10 ± 0.90	3.91 ± 0.99	4.12 ± 0.91	3.89 ± 1.01	4.15 ± 0.85	3.87 ± 0.85	4.03 ± 0.93
	F	2.918	3.327	5.934	4.319	5.448	4.783	3.060
	p	0.033*	0.019*	0.001**	0.005**	0.001**	0.003**	0.028*

Since industry differences in the characteristics of manufacturing enterprises within the context of artificial intelligence did not show a significant impact on changes in skill requirements, we conducted a comparative analysis only on enterprise size and nature. As shown in Table 3, in terms of enterprise scale, the P-values for data analysis skills, innovative problem-solving skills, and human-machine collaboration skills are all less than 0.01, indicating extreme significance. The P-values for learning and adaptability skills and interdisciplinary knowledge integration skills are 0.04, indicating significant differences. This suggests that the changes in core skill requirements among enterprises of different scales in the context of AI show clear differentiation, and these skills are trending toward becoming core requirements; Only the P-values for specialized technical skills (0.156) and AI system operation skills (0.205) did not reach statistical significance, indicating that these two types of skills are fundamental requirements for manufacturing enterprises and are not affected by differences in enterprise size. Overall, the mean skill requirements for medium-sized and large enterprises were generally higher than those for small and micro-enterprises. The most pronounced difference was in human-machine collaboration skills, with means of 4.08 and 4.06 for medium-sized and large enterprises, respectively. In innovative problem-solving skills, medium-sized enterprises had the highest value at 4.07, while large enterprises had the highest value at 4.08 for data analysis skills. This indicates the urgent need for composite skills among medium- and large-sized enterprises during their intelligent transformation.

From the perspective of enterprise nature, the P-values for all skills are less than 0.05, indicating significant or highly significant differences, which suggests that skill demand changes among enterprises of different natures are comprehensively diverging in the context of artificial intelligence. The most significant differences were observed in the P-values for AI system operation skills (0.001) and human-machine collaboration skills (0.001), with joint ventures and foreign-invested enterprises generally having higher average skill demands than state-owned and private enterprises. Regarding AI system operation skills, joint ventures (4.12) and foreign-invested enterprises (4.08) showed a significant lead; in terms of learning and adaptability, foreign-invested enterprises ranked first with a mean of 4.12; and for

interdisciplinary knowledge integration, joint ventures stood out with a mean of 4.03.

4 THE IMPACT OF ARTIFICIAL INTELLIGENCE ON EMPLOYMENT IN GUANGDONG'S MANUFACTURING ENTERPRISES

4.1 The Impact of Artificial Intelligence on Changes in Employment Scale in Manufacturing Enterprises

Table 4 Benchmark Regression Results on the Impact of Artificial Intelligence on Changes in Employment Scale in Manufacturing Enterprises

Variable	Change in Employment Scale			
	(1)	(2)	(3)	(4)
Proportion of AI R&D Expenditures	0.078** (0.039)	0.110** (0.039)	0.093** (0.039)	0.091* (0.039)
AI Investment Growth Rate	0.168** (0.040)	0.165** (0.039)	0.150** (0.039)	0.144** (0.040)
Percentage of AI Positions	0.136** (0.033)	0.129** (0.033)	0.123** (0.033)	0.112** (0.033)
AI Job Quality Assessment	0.084** (0.033)	0.085** (0.033)	0.084** (0.032)	0.077* (0.033)
Industry Type		0.079* (0.035)	0.080* (0.035)	0.081* (0.035)
Company Size			0.118** (0.037)	0.113** (0.037)
Nature of the Firm				0.090* (0.044)
N	423	423	423	423
R ²	0.069	0.075	0.086	0.091

Note: Figures in parentheses represent cluster-robust standard errors; ** and * indicate significance at the 1% and 5% levels, respectively. The same applies to Tables 5-6.

As shown in Table 4, the proportion of R&D investment in AI, the growth rate of AI investment, the proportion of AI-related positions, and the quality evaluation of AI-related positions all have a significant positive impact on changes in enterprise employment scale, indicating that the application of artificial intelligence can, to a certain extent, promote the expansion of employment scale in manufacturing enterprises. As control variables such as industry type, enterprise scale, and enterprise nature were progressively incorporated into the model, the coefficients and significance levels of the core explanatory variables remained largely stable, indicating that the model results possess good robustness. Meanwhile, the model's R² gradually increased from 0.069 to 0.091, suggesting that the inclusion of control variables has, to some extent, enhanced the model's explanatory power.

4.2 The Impact of AI on Changes in Job Demand in Manufacturing Enterprises

Table 5 Baseline Regression Results on the Impact of AI on Changes in Skilled Job Demand in Manufacturing Enterprises

Variable	Change in Job Demand			
	(1)	(2)	(3)	(4)
Proportion of R&D Investment in AI	0.127** (0.018)	0.123** (0.018)	0.114** (0.018)	0.111** (0.018)
AI Investment Growth Rate	0.115** (0.018)	0.114** (0.018)	0.106** (0.018)	0.079** (0.018)
Percentage of AI Positions	0.154** (0.015)	0.149** (0.015)	0.146** (0.015)	0.132** (0.015)
AI Job Quality Assessment	0.087** (0.015)	0.088** (0.016)	0.087** (0.015)	0.078** (0.015)
Industry Type		0.051** (0.016)	0.052** (0.016)	0.053** (0.016)
Company Size			0.063** (0.017)	0.057** (0.017)
Nature of the Firm				0.120** (0.020)
N	423	423	423	423
R ²	0.250	0.258	0.271	0.302

As shown in Table 5, the proportion of R&D investment in AI, the growth rate of AI investment, the proportion of AI-related positions, and the quality evaluation of AI positions all exhibit significant positive effects across all models. This indicates that as investment in artificial intelligence technology continues and its application deepens, the structure of corporate job demand undergoes a noticeable adjustment, with demand for technical, data-related, and intelligence-related positions gradually increasing. The coefficient for the proportion of AI personnel is relatively large, indicating that improvements in the allocation of AI positions within enterprises play a more direct role in driving changes in the job structure. As control variables such as industry type, enterprise scale, and enterprise nature were gradually incorporated into the model, the coefficients of the core variables remained generally stable, while the model's R² increased from 0.250 to 0.302. This indicates that the model's explanatory power has further strengthened, and the regression results exhibit good robustness.

4.3 The Impact of Artificial Intelligence on Changes in Skill Requirements for Manufacturing Enterprises

Table 6 Benchmark Regression Results on the Impact of Artificial Intelligence on Changes in Skill Demand in Manufacturing Enterprises

Variable	Change in Skill Demand			
	(1)	(2)	(3)	(4)
Proportion of R&D Investment in AI	0.078**(0.020)	0.078**(0.021)	0.067**(0.021)	0.065**(0.020)
AI Investment Growth Rate	0.119**(0.021)	0.119**(0.021)	0.109**(0.021)	0.105**(0.021)
Percentage of AI-related positions	0.027(0.017)	0.026(0.017)	0.023(0.017)	0.015(0.017)
AI Job Quality Evaluation	0.130**(0.017)	0.130**(0.017)	0.129**(0.017)	0.125**(0.017)
Industry Type		0.004(0.018)	0.005(0.018)	0.006(0.018)
Company Size			0.076**(0.019)	0.072**(0.019)
Nature of the enterprise				0.064**(0.023)
N	423	423	423	423
R ²	0.137	0.137	0.154	0.162

As shown in Table 6, the proportion of R&D investment in AI, the growth rate of AI investment, and the quality evaluation of AI positions all have a significant positive impact on changes in enterprises' skill demands. This indicates that the application of artificial intelligence has, to a certain extent, driven an increase in enterprises' demand for highly skilled talent and promoted the upgrading of their skill structures. However, the impact of the proportion of personnel in AI positions is not significant, possibly because the number of AI positions in enterprises is still relatively limited, and their influence on the overall skill demand structure has not yet fully manifested. As control variables such as industry type, firm size, and firm nature were progressively incorporated into the model, the coefficients and significance levels of the core explanatory variables remained generally stable, indicating that the model results possess good robustness. Meanwhile, the model's R² increased from 0.137 to 0.162, suggesting that the inclusion of control variables has, to some extent, enhanced the model's explanatory power.

5 CONCLUSIONS AND DISCUSSION

5.1 Research Conclusions

Based on survey data from 423 manufacturing enterprises in Guangdong Province, and combining analysis of variance with benchmark regression models, this study systematically reveals the multidimensional impact of artificial intelligence on employment in Guangdong's manufacturing sector against the backdrop of digital transformation. The core conclusions are as follows:

First of all, Artificial intelligence has a positive promotional effect on the scale of manufacturing employment. The proportion of AI R&D investment, the growth rate of AI investment, the proportion of AI-related positions, and the quality evaluation of AI-related positions all have significant positive impacts on changes in employment scale. Furthermore, the model results remain robust even after controlling for variables such as industry, scale, and nature, indicating that the application of artificial intelligence is not merely a matter of job displacement but rather drives a moderate expansion of employment scale.

Second, Enterprise characteristics exert significantly heterogeneous effects on employment changes. At the industry level, adjustments in employment scale are more pronounced in the equipment manufacturing and high-tech manufacturing sectors. In terms of enterprise size, changes in employment scale and structural adjustments among low-skilled workers are most notable in medium-sized enterprises (301–1,000 employees). Regarding enterprise nature, joint ventures and foreign-invested enterprises exhibit significantly greater adjustments in employment scale, demand for medium-skilled workers, and the allocation of intelligent positions compared to state-owned and private enterprises.

Third, Artificial intelligence is driving a structural transformation in manufacturing job demand. Demand for intelligent roles—such as AI R&D engineers, industrial data analysts, and smart equipment maintenance technicians—has risen significantly, while adjustments in demand for traditional roles like production line operators have been relatively gradual. Furthermore, the growth in demand for intelligent roles is more pronounced in medium-to-large enterprises, as well as foreign-invested and joint-venture enterprises.

Fourth, Artificial intelligence is driving the upgrading of manufacturing skill requirements toward a more multidisciplinary approach. Core competencies now include data analysis, human-machine collaboration, and innovative problem-solving. Demand for multidisciplinary skills is far higher in medium-to-large enterprises, foreign-invested, and joint-venture enterprises than in small, medium, and micro enterprises or domestic enterprises. Technical expertise and AI system operation capabilities remain foundational industry skills, with relatively little variation based on enterprise size; however, the impact of the proportion of AI-related personnel on overall skill demand has not yet become apparent.

5.2 Policy Recommendations

Based on the research findings, to adapt to the employment structure adjustments in Guangdong's manufacturing sector driven by artificial intelligence and to promote the coordinated advancement of high-quality manufacturing development and employment stability, the following policy recommendations are proposed at the enterprise, government, and talent development levels.

Enterprise Level: Precisely advance intelligent transformation and optimize human resource allocation. Develop differentiated transformation and staffing strategies based on enterprise characteristics. Large and medium-sized enterprises, as well as foreign-invested and joint-venture enterprises, should continue to increase investment in AI R&D, refine their intelligent job systems, and prioritize the recruitment and training of multi-skilled talent in areas such as data analysis and human-machine collaboration. Small and medium-sized enterprises (SMEs) and local private enterprises should advance intelligent upgrades in a phased manner, focusing on technological upgrades in core production processes while simultaneously conducting employee skills training to avoid talent gaps during the transition [12]; State-owned manufacturing enterprises should break through institutional constraints, optimize mechanisms for recruiting and incentivizing mid-skilled talent, and meet the demand for multi-skilled professionals capable of adapting imported technologies to local conditions. At the same time, all enterprises should adhere to the principle of "aligning technological upgrades with employment needs," utilizing internal training and job reassignments to facilitate the transition of low-skilled employees to mid-skilled positions, thereby mitigating the employment impact of the transformation [13].

Government Level: Improve the Policy Support System and Strengthen Targeted Employment Measures. Centered on the Guangdong Province Action Plan for AI-Empowered High-Quality Development of Manufacturing (2025–2027), differentiated policy support should be formulated for enterprises of varying industries, scales, and nature. For key sectors such as equipment manufacturing and high-tech manufacturing, subsidies for AI technology application should be increased; for small, medium, and micro manufacturing enterprises, special training funds for intelligent transformation and talent recruitment subsidies should be introduced. Simultaneously, establish a monitoring system for the employment structure of Guangdong's manufacturing sector to precisely track changes in job and skill demands driven by AI. For in-demand positions such as data analysis and smart equipment operation and maintenance, implement targeted training programs through collaboration among the government, enterprises, and educational institutions. Additionally, improve the social security and employment service systems to provide specialized services—including skills training and employment guidance—for employees transitioning from traditional roles, thereby alleviating structural employment conflicts [14].

Talent Development: Deepen Industry-Education Integration to Meet Upgraded Manufacturing Skill Demands. Universities and vocational colleges should adjust the curriculum of manufacturing-related programs by incorporating core content such as data analysis, AI system operation, and interdisciplinary knowledge integration. They should strengthen the cultivation of practical skills—including human-machine collaboration and innovative problem-solving—to meet the skill requirements of intelligent manufacturing roles. By deepening industry-education integration and collaborating with leading manufacturing enterprises in Guangdong to establish practical training bases, customized school-enterprise training programs can be developed for key industries such as equipment manufacturing and electronic information, thereby achieving a precise alignment between talent development and corporate job requirements [15,16]. At the same time, vocational skills enhancement training will be provided for incumbent employees, focusing on skill updates in AI application scenarios, with an emphasis on improving the digital operation and composite skills of mid-level workers, thereby building a skilled workforce suited to the digital transformation of the manufacturing sector [17].

5.3 Limitations and Outlook

Although this study examines the impact of artificial intelligence on employment in Guangdong's manufacturing sector, certain limitations exist: the survey is based on cross-sectional data, reflecting only the current state of employment at a specific point in time and failing to capture the long-term dynamic effects of technology on employment; the measurement of AI application relies primarily on quantitative indicators such as R&D investment and the proportion of AI-related positions, without considering the depth of technology adoption or differences in application scenarios; and the exploration of impact mechanisms requires further deepening.

Future research could be expanded in three areas: conducting panel data tracking studies to reveal the dynamic patterns of AI's impact on manufacturing employment; refine the metrics for measuring AI technology adoption to distinguish the heterogeneous impacts of different application scenarios and levels of technological depth, and analyze the intermediate transmission mechanisms of employment effects; and expand the scope of research to the Guangdong-Hong Kong-Macao Greater Bay Area, combining industrial cluster characteristics to explore regional and sectoral differences in AI's employment effects, while also studying the employment impacts of the synergistic application of AI and industrial robots, thereby providing empirical support for the high-quality development of manufacturing and employment synergy in the Greater Bay Area.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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