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STRUCTURAL CHARACTERISTICS AND SPATIAL DIFFERENTIATION OF TALENT DEMAND IN THE INDUSTRIAL ROBOTICS INDUSTRY IN THE GUANGDONG-HONG KONG-MACAO GREATER BAY AREA: AN ANALYSIS BASED ON JOB POSTING DATA

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Abstract—**Based on job postings from the "51job" platform in March 2025, this study employs content analysis to conduct a assessment of 866 valid positions in the industrial robotics industry across nine mainland cities in the Guangdong-Hong Kong-Macao Greater Bay Area. The aim is to examine the structural characteristics and inherent contradictions of talent demand in this industry. The findings are as follows: First, talent demand exhibits significant geographical agglomeration and functional division, with Shenzhen, Guangzhou, and Dongguan forming a synergistic chain of "R&D-transformation-application." Second, private small and medium-sized enterprises constitute the primary source of labor demand (accounting for over 80%); however, their recruitment strategies demonstrate a strong preference for "immediate combat effectiveness," overly relying on work experience as a signal. This leads to an "experience paradox" and creates employment barriers for recent graduates. Third, the educational requirement structure for talent is pyramid-shaped, with over half of the positions demanding associate degrees (53.89%), while the demand for high-end R&D talent with master's degrees or higher is less than 2%, indicating that the industry currently focuses primarily on integration and application. Fourth, salaries are positively correlated with work experience, establishing a high entry barrier for early-career professionals.**

Keywords—**Guangdong-Hong Kong-Macao Greater Bay Area, Industrial Robotics, Industry-Education Integration, Labor Market, Talent Demand Structure**

I. INTRODUCTION

Research background

Amid a new global wave of technological revolution and industrial transformation, intelligent technologies represented by artificial intelligence and robotics are reshaping the global division of labor and competitive landscape with unprecedented depth and breadth. Examining this phenomenon from the institutionalist perspective of international comparison, the talent structure challenges faced by major developed industrial robotics regions reveal not only the universal dependence of technology-driven industrial upgrading on high-skilled human capital but also the divergent development pathways shaped by different national innovation systems and institutional contexts (Witt & Jackson, 2016). Germany, leveraging its time-honored "dual system" of vocational education, has established a stable skills supply ecosystem for cultivating highly skilled "Industry 4.0" application engineers and on-site maintenance personnel (Euler, 2013). Japan, relying on its deep-rooted precision manufacturing tradition and the corporate "lifetime employment" system (Ono, 2025), has accumulated a substantial talent reserve in robot body R&D, optimization of key components, and complex process integration (Frumer, 2018). The United States, capitalizing on its strengths in basic research, innovation, and venture capital, has successfully attracted a large number of top scientists and innovative entrepreneurs (Brynjolfsson & McAfee, 2016).

Against this global backdrop, the Guangdong-Hong Kong-Macao Greater Bay Area (hereinafter referred to as the "Greater Bay Area"), as a key national economic region in

China, has been entrusted with the core mission of building "an international innovation and technology hub with global influence" (Xinhua News Agency, 2019). Compared to the a forementioned developed economies, the development path of the Greater Bay Area is distinctive: it possesses a robust manufacturing foundation, a complete industrial chain ecosystem, and dynamic market-driven innovation entities, thereby gaining global influence through market scale and industrialization speed. However, this "compressed" high-speed industrialization and technological catch-up process often leads to a lag in the upgrading and adjustment of the human capital structure, resulting in structural contradictions (Lee, 2019).

Similar to the challenges faced by Germany and Japan, the Greater Bay Area suffers from a significant shortage of "new craftsmen" and application-oriented engineers in terms of both quantity and quality. On the other hand, echoing the industrialization bottlenecks encountered by the United States, there is also a scarcity of top-tier basic R&D and original talent capable of leading industrial breakthroughs (Li, 2025). Additionally, the Greater Bay Area faces pronounced challenges in cross-city and cross-system coordination. Market fragmentation, policy disparities, and barriers to talent mobility within this "administrative region economy" exacerbate the spatial and structural mismatch of talent within the region, hindering the enhancement of overall innovation efficiency (Yang, 2021; Qi et al., 2023). This internal imbalance and differentiation are typical characteristics in the evolution of regional innovation; however, if not properly addressed, they will constrain its synergistic evolution and upgrading.

Therefore, analyzing the current state of talent demand in the core industries of this region at a specific stage of development is not only of urgent practical significance for bridging its own talent gap and optimizing the regional innovation ecosystem, but it also provides a crucial case study and theoretical reference within the Chinese context for other regions worldwide undergoing rapid industrialization and technological catch-up, such as emerging manufacturing clusters in Southeast Asia and India (World Bank, 2020), as they confront structural imbalances in human capital during technological leaps.

Research motivation

Human capital theory (Becker, 1964; Schultz, 1961) posits that the knowledge and skills individuals acquire through education and training constitute a capital investment capable of yielding future returns, directly determining their marginal productivity and wage compensation. Screening (or signaling) theory (Spence, 1973) offers a complementary perspective. This theory argues that under conditions of information asymmetry in the labor market, credentials such as educational diplomas act as "signals," conveying information about a job applicant's potential abilities to employers, though they may not necessarily equate to actual productivity. Together, these two theories explain the correlation between "education and wages," albeit with different internal logics: human capital theory emphasizes "education → enhanced productivity → higher wages," while screening theory focuses on "education → sending ability signals → higher wages" (Guan & Sun, 2020). In technology industries, particularly in the context of digital recruitment applications, the "capital attribute" and "signaling attribute" of education coexist and reinforce each other (Nikolaou, 2014).

The flow and agglomeration of talent are driven by both economic factors (such as salary and industrial opportunities) and non-economic factors (such as living environment and public services) (Florida, 2005). Within the Chinese context, talent migration exhibits characteristics of an economically dominant model, a pattern that directly shapes the distribution of human capital and competitive dynamics among cities within the Greater Bay Area (Qi et al., 2023). However, existing research focusing on the industrial robotics industry in the Greater Bay Area has significant limitations. First, most studies concentrate on macro-policy reviews or industry trend analyses, lacking the use of corporate recruitment data for investigation, resulting in a disconnect between macro strategies and micro-level market perceptions (Rana et al., 2019). Second, the majority of research discusses only the supply side (educational cultivation) or the demand side (corporate recruitment) unilaterally, failing to place both within the same framework for cross-comparison and analysis of tensions (Zhu & Cao, 2023). Third, existing studies utilizing recruitment data remain mostly at the level of descriptive statistics, failing to delve deeply into the interactive relationships between corporate attributes, scale, city location, and talent requirements.

Research objectives

This study aims to map and analyze the current state of talent demand in the Greater Bay Area's industrial robotics industry through the mining of online job market data. The research focuses on the following questions: What characteristics does this industry exhibit regarding the quantity, structure, spatial distribution, and salary pricing of talent demand? What industry stage, corporate behaviors, and structural supply-demand conditions do these characteristics reflect?

The objectives of this study are:

1. Map the Demand Landscape: Analyze the quantity of talent demand, geographical distribution, job structure, and qualification requirements (education, experience, salary) to depict the current state of industry talent demand.
2. Understand Structural Characteristics: Utilize cross-analysis to reveal the internal logic of the talent market regarding how contextual factors such as enterprise ownership, scale, and city location interact with talent requirements.

3. Assess Supply-Demand Tensions: Compare demand with the regional educational supply system to identify points and risks of supply-demand mismatch across three dimensions: level, structure, and competency.

Provide Decision Support: Offer actionable recommendations for policy optimization and strategic adjustments to governments, educational institutions, and enterprises, respectively.

II. LITERATURE REVIEW

Theoretical evolution and debates on recruitment, screening, and marketmatching

In human resource theory, recruitment is defined as "a series of activities undertaken by an organization to attract qualified applicants for vacant positions," and is viewed as a preliminary stage distinct from selection (Breaugh & Starke, 2000). However, strategic human resource management expands this concept, emphasizing that recruitment itself is a strategic process of conveying organizational signals and preliminarily screening for cultural fit. Its goal shifts from passively filling vacancies to proactively shaping a human capital structure aligned with business strategy (Cappelli & Keller, 2014).

Human Capital Theory posits that the knowledge and skills individuals acquire through education and training constitute a capital investment that enhances future productivity (Becker, 1964; Schultz, 1961). In a dialectical relationship with this is Signaling (Screening) Theory, which argues that under conditions of information asymmetry in the labor market, credentials like educational diplomas can act as "costly signals," conveying indirect information to employers about an applicant's potential ability (Spence, 1973). Together, these two theories form an explanatory framework for the "education-income" relationship. However, the internal debate over whether education primarily enhances productivity (the human capital view) or acts as an ability signal (the signaling view) remains a topic of discussion in labor economics (Autor, 2014). In the technology industry, educational credentials often play a dual role as both a "threshold signal" and a "credential of knowledge capital" (Weiss, 1995).

In recent years, research focus has expanded to the effectiveness of "experience" as an ability signal and its complementary or substitutive relationship with educational signals. Particularly in fields with rapid technological iteration, studies suggest that the signaling value of specific past experience may decay quickly, while new signals, like continuous learning ability and project outcomes, become more critical (Autor, 2015; Deming, 2017). Concurrently, the rise of the internet and digital recruitment platforms has lowered information search costs and improved matching efficiency in the talent market (Kuhn & Mansour, 2014). However, it has also sparked discussions about new forms of bias and the "skills matching gap" that algorithm-based screening may introduce (Raghavan et al., 2020). These discussions, especially research on how diversified, verifiable "proof-of-competency" signal systems can supplement or even partially replace educational signals (Nikolaou, 2021; Bills et al., 2017), provide an analytical framework for this study to understand the recruitment preferences of enterprises in the Greater Bay Area, such as their reliance on "immediate combat effectiveness" and "experience signals."

Talent market matching and diversified signal systems in the digital era

The rapid development of the internet and digital technology has spurred a transformation in recruitment models and is reshaping the matching mechanisms in the talent market. This evolution has propelled recruitment from traditional, inefficient, and fragmented offline models (Era 1.0) to an integrated online-offline Era 2.0 focused on candidate experience, and further towards a data-driven intelligent matching Era 3.0 and a platform-based Era 4.0 (Marler & Fisher, 2013). Digital recruitment platforms aggregate vast amounts of job postings and resume information, using algorithms for preliminary screening and recommendation, significantly reducing information search costs and transaction friction, thereby theoretically enhancing the efficiency and quality of job-person matching (Cober et al., 2004; Kuhn & Mansour, 2014).

This efficiency gain does not come without costs, and its derived effects have become subjects of human resource research. Increased efficiency may exacerbate the "Matthew Effect" in skill matching, making high-skilled talent easier to discover and compete for, while those with insufficient skills face more severe exclusion. On the other hand, while increasing speed, algorithmic screening may encode and amplify inherent societal biases or create new forms of discrimination, raising concerns about fairness (Raghavan et al., 2020).

In this technological context, the signal system in the talent market is undergoing a paradigm shift from "credential-based" to "performance-based" verification (Bills et al., 2017). The traditional educational diploma signal (Spence, 1973) is being supplemented, and even partially replaced, by a range of diversified, verifiable "proofs of competence" (Nikolaou, 2021). Corporate recruitment screening is increasingly shifting from assessing "general potential" to identifying "specific skills" and "immediate combat effectiveness" (Cappelli & Keller, 2013). Consequently, "strong signals" that directly demonstrate professional skills, problem-solving ability, and continuous learning potential are receiving unprecedented emphasis. Examples include specific project outcomes, awards from high-level skill competitions, traceable open-source code contribution records, and industry-recognized specific skill certifications (Bills et al., 2017).

The application of signaling theory suggests that when more low-cost, high-credibility behavioral signals are observable, employers tend to rely more on these predictive indicators for screening. However, in highly practical fields, what type of "ability signals" are most predictive? How do enterprises weigh different signals in terms of cost, reliability, and timeliness? Existing research provides insufficient answers to these key questions, especially lacking empirical evidence from contexts like China, which is undergoing rapid industrial upgrading. This study attempts to fill this gap by analyzing recruitment data from the industrial robotics industry in the Greater Bay Area, specifically examining the practical utility and combinatorial logic of emerging ability signals in this regional talent market in the digital era.

Talent demand characteristics in the industrial robotics industry

Due to its characteristics of being knowledge-intensive, technologically composite, and having a long industrial chain, the talent demand in the industrial robotics industry exhibits a distinct, multi-layered, and specialized structure globally. Analyzing from the perspective of the industrial value chain, upstream R&D and algorithms, midstream design and manufacturing, and downstream integration and application correspond to different levels of professional talent. The widespread shortage of high-skilled talent has become a global challenge (International Federation of Robotics [IFR], 2025; World Bank, 2020). The Global Value Chain perspective further suggests that industrial upgrading inherently necessitates a corresponding climb in the human capital structure towards high-value-added segments (Gereffi, 2018).

However, existing research, both international and domestic, often relies on macro-industrial reports or policy texts, lacking analysis based on corporate recruitment data. This creates a gap in understanding the real, dynamic skill demands of enterprises (Cappelli, 2015). Research focusing on the Chinese context is predominantly concentrated on macro-policy interpretation or analysis of educational supply, such as Chen & Xu (2025). The few studies utilizing recruitment data often remain at the level of descriptive statistics, failing to delve deeply into the interactive mechanisms between enterprise heterogeneity (e.g., ownership type, scale, geographical location) and talent demand structure. Furthermore, for a region like the Greater Bay Area, which exhibits clear internal development gradients and industrial specialization, there is a lack of systematic examination regarding how the "spatial mismatch" of talent supply and demand evolves and its connection to regional innovation (Cooke, 2001; Yang, 2021).

III. RESEARCH DESIGN AND METHODOLOGY

Research sample and data source

This study analyzes job postings for the industrial robotics industry published on the "51job" recruitment platform. The decision to select a single data platform is based on a careful balance between research validity and feasibility, driven by three primary considerations:

First, Market Representativeness. As a leading human resource service provider in China, "51job" holds a significant share of the online recruitment market and is a key platform for observing corporate hiring behavior (Liu et al., 2025). The platform has a wide user base in the manufacturing and technology sectors and has become a primary channel for companies in industrial robotics and smart manufacturing to post core technical and engineering positions. Thus, analyzing its data effectively captures the real dynamic demand for talent in the industry, providing an accurate reflection of the actual talent market situation (Krippendorff, 2019).

Second, Data Homogeneity and Internal Validity. By using a single authoritative platform, the study maximizes internal consistency in the data source. This approach minimizes confounding factors that may arise from differences in user demographics, information posting formats, and algorithmic recommendation logic across multiple platforms. It allows for a clearer representation of the structural characteristics of industrial talent demand, thus enhancing the study's internal validity (Neuendorf, 2016).

Third, Research Focus and Operability. The primary goal of this study is to "deconstruct" and analyze the talent demand within the industrial robotics industry in the Greater Bay Area, rather than to conduct a broad, superficial survey. Given resource constraints, selecting a platform with extensive coverage and high data quality allows for focused mining, concentrating research resources on more refined coding and analysis of unstructured text. This method is more effective for addressing research questions related to demand structure and the evolution of skill signals (Patton, 2014).

To ensure research rigor, data acquisition and cleaning followed standardized procedures for content analysis (Krippendorff, 2019), as illustrated in Figure 1.

Search Method: The primary search term was "industrial robotics," expanded to include closely related synonyms (e.g., "robotics engineer," "automation engineer," "system integration engineer," etc.). This strategy aimed to comprehensively capture functional positions across the upstream, midstream, and downstream segments of the industry chain, minimizing sample omission due to variations in corporate terminology.

Geographical Scope: The study focused on the nine mainland cities of the Greater Bay Area (Guangzhou, Shenzhen, Zhuhai, Foshan, Zhongshan, Dongguan, Huizhou, Jiangmen, Zhaoqing). Due to differences in labor market systems, recruitment platform usage habits, and data accessibility between Hong Kong and Macao, these regions were

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excluded temporarily to ensure sample homogeneity and consistency in the analytical framework.

Collection Time Point: Job postings published between March 1 and March 31, 2025, were selected. This cross-sectional data aims to capture a relatively stable "market snapshot" for analyzing talent demand structure at a specific time, avoiding potential confounding effects from seasonal fluctuations, such as peak recruitment periods after the Spring Festival or graduation seasons. This is a common method for controlling temporal heterogeneity (Miller et al., 2020). The scraped data fields included job title, company name and type, company size, work location, monthly salary range, education and work experience requirements, and job description content.

Data Filtering and Cleaning (Krippendorff, 2019): First, duplicate filtering was performed: Based on a composite judgment of job ID, company name, job title, and posting date, completely duplicate records caused by repeated company postings or platform algorithm recommendations were removed. Second, positions with extremely low relevance to the core technical functions of the industrial robotics field, such as R&D, design, integration, application, and operation/maintenance (e.g., purely administrative, general marketing, etc.), were excluded. For clearly categorized and coded information such as "company size" and "education requirement," unified assignment and standardization were applied to eliminate data noise and improve comparability.

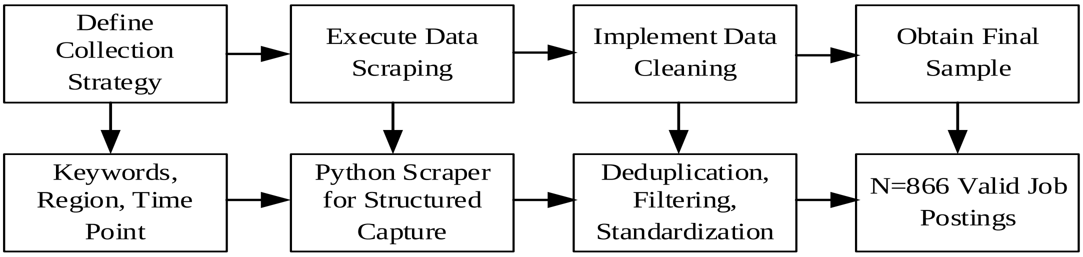

Fig. 1. Standardized process for research data acquisition and cleaning

Research methodology

This study applies content analysis to process the unstructured text of Job Descriptions (JDs). The research follows a standard procedure: defining analysis units, constructing categories, coding, and reliability testing (Neuendorf, 2016).

Analysis Units and Coding: Based on the industrial value chain and functional division, six functional position categories were constructed: "R&D/Algorithms," "Design/Integration,""Commissioning/Maintenance," "Operation/Application," "Sales/Technical Support," and "Management." Subsequently, key technical keywords were extracted from the JD text and categorized to form a skill tag library (e.g., "PLC Programming," "Machine Vision," "ROS," "Motion Control," etc.). To ensure objectivity and consistency in coding, two researchers familiar with the field conducted independent, back-to-back coding according to a coding manual. Cohen's Kappa coefficient was used to assess inter-coder reliability. After calculation, the Kappa values for all major analytical categories exceeded 0.85, indicating a high level of consistency and good reliability in the coding results (Landis & Koch, 1977).

Upon completing the text coding and quantification, the data were merged with the scraped structured fields (such as salary, education, experience, etc.) to form the final analysis dataset. SPSS software was then used for chi-square tests, frequency calculations, percentages, and measures of central tendency and dispersion. This aimed to outline the basic profile of talent demand across dimensions such as educational composition, experience requirements, salary levels, company types, and geographical distribution.

IV. DATA ANALYSIS AND DISCUSSION

Geographical distribution of talent demand in the Greater Bay Area

After filtering and deduplication, the total number of industrial robotics-related job postings on the "51job" platform was 2,558. Among these, 893 positions were located in Guangdong Province, accounting for 34.91% of all postings obtained. The nine Greater Bay Area cities provided 866 positions, constituting 96.98% of Guangdong Province's talent demand (details are shown in Figure 2). In terms of the number of job openings issued by the industry for talent demand (details are shown in Table 1), the data reveals that talent demand is highly concentrated in three cities: Shenzhen, Guangzhou, and Dongguan. Collectively, they offered 698 positions, accounting for 80.60% of the Greater Bay Area sample, and forming the core of talent demand.

An analysis of the 866 valid job posting samples revealed two interrelated characteristics: first, the quantity of talent demand shows a highly uneven spatial agglomeration in a few cities; second, these cities have formed a "R&D-Transformation-Application" division of labor pattern based on the industrial value chain. This confirms arguments from New Economic Geography regarding the spatial agglomeration of production factors to obtain external economies of scale and knowledge spillovers (Krugman, 1991). It shows that Shenzhen, Guangzhou, and Dongguan,

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through functional complementarity and synergy among cities, not only dominate in terms of demand scale but also form a highly complementary vertical division of labor in the demand structure, collectively constructing a complete industrial value chain.

Shenzhen's job demand exhibits knowledge-intensive characteristics, with over 65% of positions requiring a bachelor's degree or higher. Keywords representing the technological frontier, such as "machine vision," "SLAM," and "AI algorithms," frequently appear in the job descriptions. This positioning assigns it the role of the "innovative brain" in the industrial chain, focusing on basic research, core algorithm breakthroughs, and original innovation of high-end solutions, continuously injecting knowledge spillovers and technological vitality into the regional industry (Florida, 2002).

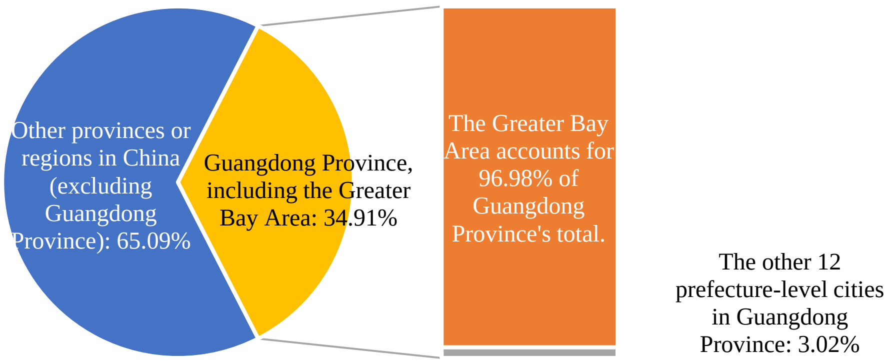

Fig. 2. Proportion of industrial robotics job openings nationwide

Table -1.Urban Distribution and Structural Characteristics of Talent Demand in the Greater Bay Area's Industrial Robotics Industry

City	Sample Count	Proportion	Core Position Type Tendency	Typical Education Requirement Focus
Shenzhen	278	32.10%	R&D/Design, High-end Integration	Bachelor's degree or above (>65%)
Guangzhou	238	27.48%	Diversified (Balanced R&D & Application)	Primarily Bachelor's, supplemented by Associate
Dongguan	182	21.02%	Integration/Commissioning, Application/Maintenance	Associate degree/Vocational diploma (~73%)
Foshan	74	8.55%	Application Implementation, Commissioning/Operation	Primarily Associate degree
Other Five Cities	94	10.85%	Basic Operation, Sales/Support	Associate degree or below

Guangzhou's talent demand structure shows significant diversification and complexity. Benefiting from its strong university research resources and mature industrial foundations in automotive and equipment manufacturing, its demand includes a considerable proportion of R&D/design positions and also encompasses a large number of system integration and industry-specific application solution roles. This characteristic of "balancing research and application" makes it a "critical transformation hub," connecting Shenzhen's original innovation with downstream large-scale manufacturing applications. Its core function lies in the engineering development, verification, and integration of complex systems (Asheim & Gertler, 2005).

Dongguan's talent demand is highly focused on the downstream of the industrial chain, with 73% of positions requiring an associate degree or vocational diploma. Skill requirements indicate expertise in robot programming, commissioning, maintenance, and integration with specific industry processes like 3C electronics. This reflects Dongguan's role as a world-class manufacturing base. Its core function is as the "industrialization body," responsible for the scaling and implementation of upstream technological solutions. It serves as the execution end and skill implementation site where industrial value is realized (World Bank, 2020).

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This study conducted a chi-square test of independence between the variables "City" (Shenzhen, Guangzhou, Dongguan) and "Position Functional Type" (R&D, Design/Integration, Application/Maintenance, etc.). The results confirmed a statistically significant association between the two ($\chi^2(df)=215.34$, $p < .001$). This effectively supports the conclusion that a systematic and structured industrial geographical division of labor has formed within the Greater Bay Area, thereby validating the research conclusions of scholars such as Yang (2021), Xu et al. (2021), and Zhu (2021) regarding regional synergy mechanisms.

Private enterprises dominate the labor demand market

Among the 866 valid job postings, private enterprises offered 703 positions, accounting for 81.18% of the total. Their demand intensity is 5.2 times that of the combined demand from foreign-invested, joint-venture, and state-owned enterprises, which totaled 135 postings (details are shown in Figure 3). This confirms the role of private enterprises in driving the development of China's emerging industries.

Analysis of recruitment behaviors among enterprises with different ownership types reveals that private enterprises' hiring practices embody the logic of "rational choice under resource constraints." Under intense market competition and survival pressures, private firms tend to adopt the most cost-effective strategy: prioritizing the recruitment of application-oriented talent with "immediate combat effectiveness" (typically requiring 1-5 years of relevant experience) to respond swiftly to market demands and meet project delivery deadlines (Cappelli & Keller, 2014). This behavioral pattern can be explained by Signaling Theory: in an information-asymmetric talent market, private enterprises regard "past relevant work experience" as a more reliable and direct indicator of ability than initial educational credentials, thereby minimizing the risk of selection errors and the immediate costs associated with internal training (Spence, 1973).

In contrast, although foreign-invested/joint-venture and state-owned enterprises offer fewer positions, their recruitment strategies focus on the high-end and standard-setting segments of the industrial chain (details are shown in Table 2). They place greater emphasis on candidates' long-term development potential, and their requirements for higher education and advanced research capabilities highlight their strategic roles in fundamental R&D and system integration.

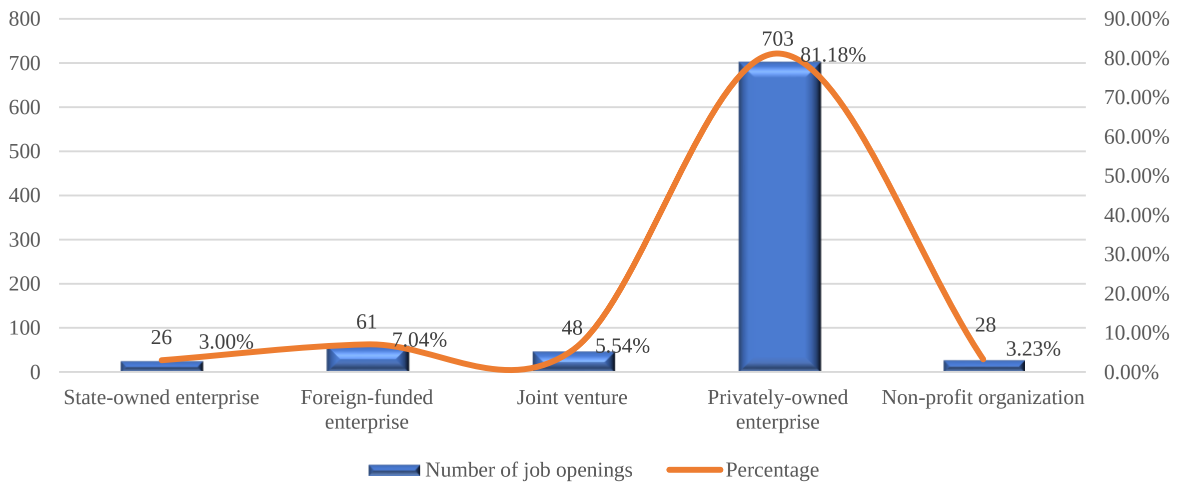

Fig. 3. Distribution of company ownership types and corresponding job opening counts in the Greater Bay Area's industrial robotics industry

In the rapidly evolving technological industry environment, the role of traditional educational diplomas as a "signal of general potential" is relatively weakened on the application side. This role is increasingly being replaced by "verifiable, specific ability signals," such as concrete project outcomes and operation certifications for specific brand equipment (e.g., FANUC/ABB) (Bills, 2004). This marks an evolution of the screening mechanism from academic thresholds to a diversified, performance-based proof system.

Despite being the largest source of demand for such talent, the strong "rapid application" orientation of private enterprises may lead them to consume employees' existing skills without the incentive to invest in their continuous, cross-domain skill development (Acemoglu & Autor, 2011). This widespread short-sighted strategy of pursuing "finished talent" rather than "investing in potential" may erode the willingness and capacity within the industry to cultivate talent pipelines autonomously, thereby endangering the continuity of technology inheritance and innovation (Cappelli, 2009). The potential consequence is that the supply of "new craftsmen" may meet the quantitative demand but stagnate in qualitative depth and innovative capability, leading to a skill lock-in dilemma characterized by "craftsmanship without innovation," which hinders continuous industrial upgrading and value enhancement (World Bank, 2020).

Analysis of the recruiting enterprise scale structure reveals that talent demand is highly concentrated in small and medium-sized enterprises (SMEs). This distribution not only reflects the industry's current phase of rapid growth and market structure formation but also indicates its inherent vitality and potential structural fragility.

Table -2.Comparison of talent demand characteristics among enterprises of different ownership types in the Greater Bay Area's industrial robotics industry

Dimension	**Private Enterprises**	**Foreign/JV/State-Owned/Non-Profit Organizations**
Core Strategic Orientation	Market responsiveness & rapid application	Technology leadership & long-term planning
Proportion of Job Openings	703 (81.18%)	163 (18.82%)
Education Requirement	Primarily associate degree (~58%), supplemented by bachelor's+ (~35%)	Primarily bachelor's degree or above (>70%)
Work Experience Requirement	Highly concentrated in 1-5 years (>85%), emphasizing "immediate combat effectiveness"	Wider distribution, requiring 5+ years of senior experience for high-end positions
Typical Ability Keywords	Independent problem-solving, adapting to fast pace, on-site commissioning, project delivery	Foresighted technology research, large-scale system integration, industry standards, core technology breakthroughs
Compensation Features	Wide distribution range; concentrated intervals (e.g., 4.5k-10k RMB) reflect cost sensitivity & flexible incentives	Overall higher median; significant salary premium for core positions (avg. ~18% higher than similar positions in private firms)

Small and medium-sized enterprises as the main force of talent demand

SMEs with fewer than 500 employees constitute the primary source of talent demand, offering a total of 712 positions, which accounts for 82.18% of the overall demand. Particularly active are high-growth enterprises with 50 to 150 employees, which provided 348 positions (40.16%), representing the most dynamic segment of market demand. In contrast, enterprises with over 1,000 employees demonstrated relatively stable demand, with a combined total of only 94 positions (10.88%), primarily focused on filling key roles and ensuring a strategic reserve of high-end talent (details are shown in Table 3).

Table -3.Distribution and phase characteristics of talent demand in the industrial robotics industry by enterprise size

Enterprise Size (Number of Employees)	**Number of Job Openings**	**Proportion**
Under 50	187	21.53%
51 - 150	348	40.16%
151 - 500	177	20.49%
501 - 1000	60	6.94%
1001 - 5000	66	7.64%
5001 - 10000	2	0.23%
Over 10001	26	3.01%

SMEs (including system integrators, specialized solution providers, and tech startups) represent the backbone of the industrial robotics ecosystem in the Greater Bay Area. They drive technology commercialization, business model innovation, and meet the long-tail demands of the market, thereby generating a substantial volume of job demand. In contrast, the recruitment activities of leading enterprises have progressed beyond mere scale expansion. Their human resource strategies are increasingly focused on attracting highly specialized "top-tier talent" to reinforce their competitive advantages and industry leadership.

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Compared to large enterprises, the recruitment behavior of SMEs reflects a rational choice under resource constraints, emphasizing a preference for practical, application-oriented talent with "immediate combat effectiveness" (Cappelli & Keller, 2013), a trend that is both consistent and mutually reinforcing. The study finds that positions offered by SMEs require a significantly higher proportion of candidates with "1-3 years of work experience." This phenomenon can be explained through the lenses of Transaction Cost Theory and Signaling Theory.

For SMEs confronting relative scarcity in capital, time, and management resources, the marginal cost of a failed hire is extremely high. Thus, "possession of directly relevant project experience" becomes the most reliable and economical signal for assessing ability. Enterprises use this criterion to quickly identify candidates with immediate combat effectiveness, aiming to maximize the certainty and return on investment in human resources (Spence, 1973; Williamson, 1981). Furthermore, many SMEs have not yet established internal training and development systems. Under the dual pressures of survival and growth, they are more inclined to recruit ready-made human capital from the external talent market rather than engage in the lengthy, high-risk process of internal "cultivation." This approach externalizes the responsibility and risk of human capital investment onto employees' previous employers or the public education system (Becker, 1964).

This widespread, survival-pressure-driven "experience preference" creates a structural contradiction with the need for a large-scale infusion of fresh talent required for the industry's sustainable development. It inadvertently raises entry barriers to the industry, exacerbating the "first-job dilemma" for junior talent and recent graduates. In the long term, this may diminish the breadth and diversity of the industry's talent pool (Paul & Scott, 2011).

The Industry's mainstream has not yet entered high-end R&D

Analysis of educational requirements for job postings reveals a stable and distinctly characterized structure. Regarding the educational levels demanded by employers, 467 positions (53.88%) require only an associate degree, 307 positions (35.45%) require a bachelor's degree, 74 positions (8.50%) require a high school diploma or a secondary specialized school diploma, 11 positions (1.30%) require a master's degree, and 5 positions (0.58%) require a doctoral degree (details are shown in Table 4). The demand is greatest for associate degrees, followed by bachelor's degrees; the combined proportion for higher-degree talent such as master's and doctoral degrees is only 1.30% + 0.58% = 1.88%. Considering the increasing daily demand for application-oriented talent in the industrial robotics industry for installation, commissioning, maintenance, operation, and design/development, as reflected in these educational requirements, it is evident that the current industry mainstream remains concentrated in production and application-oriented positions. The focus is still on integration, application, and large-scale implementation, rather than on fundamental theory and cutting-edge R&D.

The reasons for the demand for high-degree talent being less than 2% are as follows:

First, the low demand for high-degree talent can be attributed to two factors. Constrained by resources, the majority of private SMEs have relatively insufficient investment in R&D and high-end equipment, which directly suppresses demand for high-end R&D talent (Li et al., 2022). Second, from the perspective of the industrial development stage, the main body of the current industrial robotics industry remains in the phase of technology integration and large-scale application, and has not yet fully entered the high-end domain requiring extensive fundamental research and original breakthroughs. Consequently, this has not significantly driven market demand for top academic talent.

Second, the demand for associate degrees exceeding half reflects the industry's thirst for large-scale, high-quality "new craftsmen." These positions constitute the critical execution layer for realizing technology implementation and ensuring production stability and efficiency. Furthermore, the coexistence of high-degree talent's scarcity and high concentration reveals the bottlenecks and direction of industrial upgrading. The less than 2% demand for master's/doctoral degrees does not imply the industry lacks a need for innovation; rather, it indicates that breakthrough innovation activities are concentrated in only a few positions, namely in R&D centers in Shenzhen and Guangzhou, as well as the cutting-edge departments of leading enterprises. Their scarcity reflects the caution of most enterprises regarding R&D investment and illustrates the need for the Greater Bay Area to strengthen the construction of a complete innovation chain from "original innovation" to "pilot-scale verification."

This study finds that the current talent market exhibits a dualistic educational signaling system: at the broad application layer, the role of education as a "signal of general potential" is relatively weakened; corporate screening heavily relies on "verifiable, specific ability signals" such as certifications for specific equipment, project outcomes, etc. (Bills, 2004; Spence, 1973). However, at the core innovation layer, high-end educational credentials, represented by "prestigious university master's/doctoral degrees," remain the "hard currency" for proving high intellectual capital and gaining entry into key R&D domains, due to their high acquisition cost and rigorous screening process. Their screening mechanism remains robust and stringent.

In summary, the current application-skill-dominated talent demand structure reflects both the industry's development reality and highlights structural contradictions in talent supply and demand. It confirms the shortage of high-end R&D talent and composite "new craftsmen," while substantial demand remains concentrated in the technology application and integration segments. If this structure persists long-term, it may lead to the industry being locked into product competition with lower added value, facing risks of technological path dependency and sluggish upgrading (Arthur, 1989). Despite strong policy pushes for industrial advancement to the high end in China and Guangdong, the current signals released by the market in terms of compensation and job postings still strongly favor immediately applicable, application-oriented skills. This presents a challenge to the higher education system, potentially causing a cognitive mismatch between training objectives and market demands. It also tests the vocational education system's ability to cultivate "immediate combat effectiveness" while solidifying students' capacity for sustainable learning, to cope with rapid technological iterations and avoid falling into the trap of "skill obsolescence" (Acemoglu & Autor, 2011).

Table -4. Multidimensional analysis of the educational demand structure for talent in the Greater Bay Area's industrial robotics industry

Educational Level	**Number of Positions (Proportion)**	**Corresponding Position Direction**	**Core Competency Requirements & Industry Segment**	**Screening Logic from a Signaling Theory Perspective**
Doctoral/Master's	16 (1.9%)	Design/R&D: Algorithm Engineer, Core Component R&D Scientist.	Fundamental research and original innovation. Concentrated in top enterprise research institutes or university labs, solving "from 0 to 1" problems.	Uses prestigious institution diplomas, high-level papers/patents as hard thresholds to screen individuals with potential for long-term, high-risk R&D investment.
Bachelor's	307 (35.45%)	Design/R&D / Integration/Application: Mechanical/Electrical Design Engineer, Systems Engineer, Project Manager.	System design and engineering management. Acts as the "bridge" connecting cutting-edge R&D with on-site application, responsible for problem modeling and lifecycle management.	Educational credentials signify that candidates have undergone scientific/engineering training, serving as a basic requirement for competent and creative tasks.
Associate Degree	467 (53.9%)	Integration/Application / Service Promotion: Commissioning Engineer, Automation Technician, After-sales Support, Production Line Maintenance.	Process implementation and on-site operation/maintenance. Corresponds to the core "application implementation" downstream, requiring proficiency with specific equipment, processes, and troubleshooting.	The combination of an "Associate Degree" with "skill certificates/project experience" forms an efficient screening method. The core is assessing immediate combat effectiveness and skill proficiency.
High School/Vocational Diploma	74 (8.5%)	Operation & Basic Maintenance: Robot Operator, Assembler.	Execution of standardized processes and routine maintenance. Performs basic, highly repetitive and programmed tasks.	Completion of basic vocational education, meeting position compliance and operational safety requirements.

Correlation between compensation and work experience

This study, through cross-analysis of compensation and work experience requirements, reveals the core pricing logic and screening mechanisms within the industry's talent market. A significant positive stepwise relationship is found between compensation levels and work experience requirements. This not only confirms the principles of Human Capital Theory but also highlights the pragmatism and risk-aversion tendencies in the recruitment strategies of enterprises during the industry's growth phase, as well as the employment difficulties resulting for entry-level talent.

Regarding monthly salaries, it is observed that the compensation offered by enterprises is generally concentrated in the range of 4,501 to 10,000 RMB, covering approximately 56.55% of the positions. Among these, positions with monthly salaries exceeding 8,000 RMB account for 46.70%, indicating that the market provides moderately high compensation for labor possessing certain skills. However, high-end positions with monthly salaries above 20,001 RMB constitute only 6.03%, and those above 30,000 RMB a mere 1.16% (details shown in Table 5). This, from a compensation perspective, reaffirms the scarcity of high-end positions in the industry's value chain.

Table -5. Talent compensation and corresponding job openings in the Greater Bay Area's industrial robotics industry

Monthly Salary (RMB)	**Number of Job Openings / Proportion**
Below 4,500	124 (14.37%)
4,501-6,000	174（20.05%）
6,001-8,000	164（18.89%）
8,001-10,000	152（17.61%）
15,001-20,000	59（6.72%）
20,001-30,000	52（6.03%）
Above 30,001	10（1.16%）

The correlation between compensation and work experience is one of the clearest signals in the talent market. Individuals with 1-3 years of work experience represent the highest demand group (48.77%) (details shown in Table 6). Their corresponding compensation is mostly concentrated in the 6,001-10,000 RMB range, marking the transition from "novice" to "skilled worker" and the associated pay increase. Possessing 3-5 years of work experience becomes a critical node for significant salary advancement. Engineers with this level of experience are typically capable of independently overseeing modules or projects. Their median salary is significantly higher than that of those with 1-3 years of experience and often falls within the 10,000-20,000 RMB range, reflecting an "experience premium."

Table -6. Work experience requirements and corresponding job openings in the Greater Bay Area's industrial robotics industry

Work Experience	**Number of Job Openings / Proportion**
1-3 years	424（48.77%）
3-5 years	234（27.00%）
5-10 years	113（13.00%）
Over 10 years	78（1.69%）
No requirement	17（9.54%）

Those with over 5 years of experience fall into the category of senior experts or technical managers. Although market demand for them is relatively smaller (~14.69%), they possess the strongest bargaining power and constitute the main candidate pool for high-salary positions above 20,000 RMB. In contrast, the demand for positions requiring "no experience," particularly targeting fresh graduates, is extremely low (less than 2% in the sample). Their starting salaries are primarily concentrated in the 4,500-6,000 RMB range, reflecting the general unwillingness of enterprises to bear high costs during employees' "skill conversion period."

According to Becker's theory, work experience represents a form of specific human capital accumulated through "learning by doing." These skills and tacit knowledge, highly relevant to the enterprise or position and formed on the job, can directly enhance an employee's marginal productivity (Becker, 1964). Therefore, the willingness of enterprises to pay a premium for experience is essentially a market compensation for this verified productivity reserve that can create immediate value. Compared to the educational diploma of a new graduate, experience conveys richer and more reliable information to the employer: it not only proves

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that the candidate possesses basic professional qualities and can adapt to the organizational environment, but also directly indicates that their acquired skills have practical value validated by the market. For enterprises, hiring experienced employees significantly saves training costs, achieves "plug-and-play," and thereby reduces the risk of a failed hire (Paul & Scott, 2011). This reliance on the experience signal is a rational economic decision made by enterprises (especially resource-constrained SMEs) in an uncertain environment. In the information-asymmetric talent market, past work experience constitutes a strong, observable, and verifiable signal (Spence, 1973).

Secondly, salary figures in Shenzhen are noticeably higher than in other cities like Guangzhou and Dongguan. For the same position (e.g., "Robotics Application Engineer"), the average salary offer in Shenzhen is 15%-25% higher than in Dongguan. This disparity cannot be fully explained by differences in urban living costs alone. Its underlying cause lies in the differentiation of industrial sophistication and innovation density between cities. According to New Economic Geography and Compensating Wage Differential Theory, Shenzhen occupies higher value-added, more complex R&D and innovation segments within the industrial chain, creating more urgent demand and fiercer competition for high-skilled talent (Krugman, 1991; Moretti, 2013). Therefore, the salary differential is a monetary manifestation of urban industrial positioning and talent scarcity. Acting as a powerful market signal, it guides the flow of human capital towards innovation cores with higher value chain positions and more significant knowledge spillover effects (Florida, 2002), further reinforcing the "core-periphery" functional division of labor pattern within the region.

V. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Through the analysis of data from the "51job" recruitment platform, this study reveals the structural characteristics and inherent contradictions of talent demand in the industrial robotics industry within the Greater Bay Area. The findings indicate that the talent challenges facing this industry are far from a simple quantitative shortage; rather, they represent a highly structured, contextual, and systemically tense supply-demand mismatch. The key findings can be summarized into four interconnected and progressively layered issues:

First, the Greater Bay Area has formed a clear, geographically-based industrial chain division of labor. Shenzhen focuses on innovative R&D (with over 65% of positions requiring a bachelor's degree or higher), Guangzhou plays a pivotal role in R&D transformation and system integration, while Dongguan, Foshan, and other cities dominate large-scale integration and application implementation (with 73% of positions requiring an associate degree or lower). This "R&D-Transformation-Application" division is a hallmark of the regional industrial chain. However, the current distribution of educational resources and the spontaneous labor market flow are not fully aligned with this spatial specialization, leading to misalignment between talent supply and demand in terms of both geographical space and skill structure, which weakens regional synergistic efficiency.

Second, private enterprises contribute over 80% of job demand and serve as the core engine of industrial vitality. Yet, their recruitment behavior exhibits a strong tendency to "avoid training risks and pursue immediate job readiness." Over 85% of positions require 1-5 years of work experience, while demand for inexperienced fresh graduates is extremely low (< 2%). This essentially externalizes the initial human capital investment cost of transforming an employee from a "learner" to a "producer," creating a typical "market failure." Enterprises are caught in a competition for "skilled workers," while the education system produces a large number of graduates who experience "difficulty entering the field." Although this strategy may reduce enterprise costs in the short term, it suppresses the autonomous cultivation of internal talent pipelines and the foundation for technological innovation in the long run.

Third, the distribution of educational requirements for talent presents a stable pyramid structure (Associate degree: 53.89%, Bachelor's: 34.45%, Master's/PhD: 1.88%), indicating that the industry is currently still driven by integration and application. However, this structure conceals a severe imbalance: there is a simultaneous shortage of both top-tier foundational R&D leaders (Master's/PhD) and mid-tier high-end composite "new craftsmen." The shortage of R&D leaders restricts the industry's ability to ascend the value chain, while the lack of mid-tier new craftsmen limits the high-quality transformation and upgrading of technological achievements, exposing the industry to the risk of a "hollowing out" of the middle tier.

Fourth, the analysis shows a positive correlation between compensation levels and work experience requirements, consistent with Human Capital Theory; however, this concurrently constructs an "experience barrier." The squeeze on "no experience" positions combined with their low starting salaries creates a significant obstacle for entry-level talent. This not only dampens the enthusiasm of potential practitioners but also leads to a loss of diversity and innovative vitality within the industry, forming a paradox where "enterprises are eager for talent" coexists with "graduates having nowhere to start."

Recommendations

Based on the a forementioned research findings, the following recommendations are proposed:

First, the government should strengthen regional policy coordination and promote the establishment of a "Greater Bay Area Talent Shared Pool" alongside a targeted talent flow mechanism between "Innovation-Application." Through measures such as tax incentives and subsidies, enterprises (especially private SMEs) should be encouraged to jointly establish training bases with universities and vocational colleges and conduct order-based training programs. This would help share the training costs for entry-level talent and address the "experience paradox." Concurrently, guided by the regional "R&D-Transformation-Application" division of labor, educational resources should be allocated differentially. Support should be directed toward Shenzhen and Guangzhou to strengthen the cultivation of high-end R&D talent, while Dongguan, Foshan, and other areas should focus on nurturing high-quality "new craftsmen." This would promote the dynamic alignment of talent supply with the spatial industrial structure.

Second, educational institutions (universities and vocational colleges) should accelerate the reform of curriculum systems and strengthen industry-education integration. Universities need to break down disciplinary barriers, develop interdisciplinary projects such as "AI + Robotics," and enhance students' system integration and innovation capabilities. Vocational colleges should remain closely aligned with industrial technologies, promptly update training equipment and course content, and incorporate industry certifications and project practice outcomes into the talent evaluation system to strengthen graduates' "verifiable skill signals." Furthermore, the widespread implementation of "corporate mentorship programs" and "modern apprenticeship systems" should be promoted to create conditions that allow students to accumulate practical experience.

Third, enterprises (especially private companies) should shift away from the short-sighted strategy of over-relying on externally sourced "finished talent" and instead focus on building internal talent development systems to enhance their long-term competitiveness. Strategies such as establishing "internship positions," conducting internal training, and creating technical career progression paths can be employed to proactively invest in potential talent. Leading enterprises should play a demonstrative role by sharing training resources with SMEs within their ecosystem to collectively enhance the depth and sustainability of the industry's talent foundation.

Research limitations and future outlook

First, there are limitations regarding data sources. The data for this study primarily originates from the single recruitment platform "51job." Although this platform possesses high market representativeness, reliance on a single channel may not encompass all types of enterprises and recruitment methods (such as corporate websites, internal referrals, vertical industry recruitment platforms, etc.). This may lead to biases in the coverage of enterprise types and position levels in the sample. Future research could employ data triangulation by integrating multiple recruitment platforms, official corporate recruitment pages, and even administrative data such as social security or tax records. This would help construct a more comprehensive and multi-dimensional image of talent mobility and demand, thereby enhancing the external validity of research findings.

Second, there are limitations in research design. This study is based on cross-sectional data, which effectively portrays the static structure of talent demand at a specific point in time. However, this design struggles to capture the dynamic evolution of the industry and cannot test causal relationships between variables. For instance, it does not analyze the dynamic impact mechanisms of economic cycle fluctuations or major technological breakthroughs (e.g., the proliferation of large AI models) on the specifications and quantity of talent demand. Future longitudinal tracking studies or case studies could address this limitation. Through long-term time-series data or process tracing, they could reveal the causal links between industrial transformation and the evolution of talent demand more clearly.

Third, there are limitations in explanatory depth. This study has shortcomings in explaining deep-seated motivations and complex mechanisms. Although it identifies the prevalent enterprise preference for "light on training, heavy on immediate readiness," it fails to delve deeply into the decision-making logic, organizational constraints, and institutional context behind this preference. Is it driven by cost avoidance under survival pressure, concern over risks from rapid technological iteration, or a lack of internal incentive mechanisms? To address this gap, future qualitative research (such as in-depth interviews with enterprise HR decision-makers, technical department heads, and senior engineers) is essential. By employing qualitative methods, the micro-level motivations and meso-level organizational contexts behind recruitment behaviors can be explored in depth. This approach would provide richer, more process-oriented explanations for phenomena such as the "experience paradox" and "skill lock-in," achieving a complementary understanding that integrates quantitative phenomenon revelation with qualitative insight.

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