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Adaptive Strategies under Structural Mismatch: A Regional Heterogeneity Analysis of AI Talent Demand in Enterprises of the Guangdong-Hong Kong-Macao Greater Bay Area

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Abstract

The rapid development of the artificial intelligence (AI) industry is profoundly reshaping the supply-demand dynamics of regional labor markets. This study focuses on Guangdong Province's Guangdong-Hong Kong-Macao Greater Bay Area, a key hub of China's AI industry, and aims to address a critical question: What kind of talent do enterprises truly need within this vast and diverse industrial ecosystem? By analyzing data from 213 AI-related job postings on the "Izhanchi" recruitment platform and employing descriptive statistics and text mining methods, the study reveals several key findings: First, talent demand is highly spatially concentrated within the Greater Bay Area, forming a pattern characterized by "Guangzhou and Shenzhen as dual cores leading the way, with Foshan and Dongguan collaborating in a tiered manner." Each city develops differentiated human capital needs based on its industrial endowments. Second, the labor market demonstrates a preference for "young talent with engineering potential and high learning resilience." The generalized label of "Algorithm Engineer" highlights the core demand for methodological capabilities during the industry's implementation phase. Enterprises' recruitment of recent graduates is, in essence, a long-term strategic investment aimed at building specific human capital. Third, the market signaling mechanism has undergone adaptive evolution, with practical signals such as "project experience" gaining prominence. Additionally, salary pricing indicates that the combination of technical proficiency, domain integration capability, and human-complementary skills is key to securing market premiums. This study underscores that the "shortage of effective supply of engineering-oriented human capital" is the underlying cause of current challenges and provides a foundation for policy insights aimed at constructing an industry-education collaborative human capital development ecosystem.

Keywords: *AI Talent Demand; Domain Integration Capability; Engineering Capability; Industry-Education Collaboration; Recruitment and Deployment; Structural Supply-Demand Mismatch*

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1. INTRODUCTION

1.1. Research Background

Artificial intelligence (AI), as the core driving force behind the new round of technological revolution and industrial transformation, is reshaping the structure, skill demands, and occupational landscape of the global labor market with unprecedented breadth and depth (Acemoglu & Restrepo, 2018). Amid this global wave, AI technological capabilities have become key factors for countries vying for strategic dominance in science and technology, with their development closely linked to national economic paradigm shifts and long-term competitiveness. The Chinese government attaches great importance to the strategic position of AI, having issued a series of policy documents, including the “Internet + AI Three-Year Action Implementation Plan” (National Development and Reform Commission et al., 2016), the “Three-Year Action Plan for Promoting the Development of the New Generation AI Industry (2018-2020)” (Ministry of Industry and Information Technology, 2017), and, most recently, the State Council’s “Opinions on Deepening the Implementation of the ‘AI+’ Initiative” (State Council of the People’s Republic of China, 2025). These policies systematically plan the industrial ecosystem with the aim of enhancing the country’s comprehensive strength in global technological competition.

Guangdong Province, particularly its core region, the Guangdong-Hong Kong-Macao Greater Bay Area (hereinafter referred to as the Greater Bay Area), has become a frontline for the development and application of China’s AI industry, thanks to its robust manufacturing base, vibrant innovation environment, and open market. Under the strategic layout of “dual-city drive, region-wide coordination,” an application ecosystem has begun to take shape, with Shenzhen (technological innovation and rapid industrialization) and Guangzhou (comprehensive R&D and frontier exploration) serving as the core engines, radiating to manufacturing clusters in cities such as Foshan and Dongguan (Guangdong Provincial People’s Government, 2025; Department of Science and Technology of Guangdong Province, 2023). With the rapid expansion of the industry and increasing complexity of technological pathways, talent demand has exhibited significant differentiation and heterogeneity in both geographical distribution and competency dimensions. In response, Guangdong Province’s policies explicitly emphasize the need to “precisely focus” on attracting and cultivating high-skilled and urgently needed professionals (in-demand talent), regarding high-quality human capital as a core strategic resource for building the region’s enduring industrial competitive advantage (Guangdong Provincial People’s Government, 2025; General Office of the Guangdong Provincial People's Government, 2025).

However, the rapid iteration and deepening application of the AI industry have increasingly highlighted the structural contradictions between talent supply and demand. On one hand, the industry is transitioning from single technological applications to full-chain collaboration covering “basic research—technological development—engineering implementation—commercial operation.” This shift has spurred demand for composite high-end talent (versatile high-end talent) who are not only proficient in cutting-edge algorithms but also possess deep expertise in specific industries and engineering practices (e.g., MLOps). Such talent is experiencing an evident “structural shortage” (Guo et al., 2024). On the other hand, higher education systems, as the primary source of talent supply, often lag behind the rapid evolution of technology in terms of curriculum design, training models, and knowledge updates. This results in a “skills mismatch” between the skill sets acquired by graduates and the rapidly changing specific needs of the industry (Li & Chen, 2025; Xu et al., 2021).

Therefore, this study focuses on a practical question: What are the real talent demands of enterprises within Guangdong Province’s diverse and dynamically evolving AI industrial ecosystem? Specifically, what are the characteristics of the required talent’s competency profile (technical, methodological, and literacy), geographical distribution, and market value (e.g., salary levels)? Exploring this issue is not only an accurate depiction of regional industrial talent demand but also a critical link connecting national strategic guidance, regional industrial development planning, and educational talent cultivation practices. It aims to diagnose and provide key suggestions for addressing current talent bottlenecks.

1.2. Research Motivation

This study arises from the pressing need to bridge three critical gaps currently existing between academic discourse and industrial practice in the field of AI talent.

Firstly, there is the "cognitive gap" between macro-level trend judgments and micro-level demand insights. Existing research predominantly focuses on macro-level narratives, such as national industrial policy analysis or global talent mobility, while empirical studies based on real-time, dynamic corporate recruitment data—specifically examining the structure, scale, and immediate changes in AI talent demand in concrete regions like the Greater Bay Area—remain insufficient. This lack of micro-level insight often causes relevant discussions to become overly generalized. This study aims to provide objective micro-level evidence to support macro-level judgments by mining highly current online recruitment data.

Secondly, there is the "matching gap" between talent cultivation on the supply side (educational institutions) and talent utilization on the demand side (enterprises). The "disconnect between learning and application" is widely recognized as a core issue constraining the effective supply of AI talent (Li & Chen, 2025; Xu et al., 2021), as the updating speed of university curricula often lags behind rapid technological iteration. By deconstructing the "capability requirements" implicit in corporate recruitment texts, this study hopes to provide direct and objective market signals and evidence for optimizing disciplinary design, course content, and teaching methodologies, thereby promoting reform on the educational supply side.

Finally, there is the "effectiveness gap" between macro-level talent policies and their micro-level implementation. Although Guangdong Province has introduced a series of policies guiding AI industry and talent development (Guangdong Provincial People's Government, 2025), maximizing their effectiveness hinges on whether these policies can accurately identify and respond to the genuine pain points and structural contradictions faced by market entities. This study strives, through a combination of quantitative and qualitative analysis, to delineate a clear talent demand map and competency model. It aims to provide empirically based decision-making support for relevant government departments in designing more targeted, synergistic, and actionable policy instruments.

1.3. Research Objectives

This study is structured around the progressive logic of "macro-level landscape characterization → micro-level specification

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deconstruction → policy pathway construction," aiming to achieve a complete research cycle that moves from describing phenomena to analyzing mechanisms, ultimately serving practical improvement.

First, this study will characterize the structural features of macro-level demand, focusing on analyzing the overall scale of talent demand, the spatial distribution patterns (particularly the clustering and diffusion patterns within the Greater Bay Area), and the composition of job types. The goal is to uncover the intrinsic relationship between spatial organization logic and regional industrial division of labor (Florida, 2002).

Second, the study will conduct an in-depth deconstruction of the competency profiles of micro-level positions. Moving beyond job titles, text mining techniques will be employed to analyze the composite requirements of enterprises for job applicants regarding both explicit qualifications (education, experience) and implicit capabilities. This includes specific aspects such as core technical skills (e.g., programming languages and algorithm frameworks) and comprehensive competencies (e.g., collaboration, innovation, and complex problem-solving abilities). Through this, the study aims to construct a multi-dimensional, realistic talent competency portrait based on genuine market signals (Lwakatare et al., 2021).

Finally, the study is committed to bridging the cultivation and policy pathways through industry-education collaboration. By translating the above findings into practical guidance, it seeks to diagnose key mismatches in talent supply and demand. It will propose targeted and actionable recommendations for the reform of higher education and vocational training systems, strategic adjustments in corporate human resource practices, and the precise design and coordinated governance of government industrial and talent policies.

1.4. Research Methodology

This study adopts a mixed-method research design that combines quantitative and qualitative approaches. Through a multi-stage analysis of recruitment data, it aims to reveal the landscape and underlying logic of regional AI talent demand from three levels: macro-level depiction, meso-level deconstruction, and micro-level insight.

1.4.1. Data Source and Sample

The "Izhanchi" recruitment platform was selected as the primary data source, primarily based on the following three considerations: First, the platform is jointly guided by institutions such as the Guangdong Provincial Committee of the Communist Youth League, the Guangdong Provincial Department of Education, and the State-owned Assets Supervision and Administration Commission of Guangdong Province. It is deeply dedicated to serving youth internships and employment within the province, making the job postings on the platform effective reflections of the official recruitment intentions of legitimate enterprises in the region. The data thus possess high policy relevance and external validity. Second, the platform has served over 150,000 enterprises and more than 30 government agencies, providing broad sample coverage that helps capture overall market dynamics. Finally, the platform utilizes AI technology to standardize job information, offering a solid foundation for subsequent structured text analysis (Izhanchi, 2025). This purposive sampling strategy aims to obtain sample data highly relevant to the research questions and controlled for quality (Creswell & Poth, 2017).

1.4.2. Data Processing and Cleaning

The data collection window was set from November 1 to 15, 2024, to focus on core demand released during the peak autumn recruitment period of the year. To ensure samples strictly belonged to AI industry-related positions, filters such as "Full-time" and "Onboard within one week" were applied, combined with keyword searches including "AI," "Algorithm Engineer," and "machine learning." After obtaining the initial sample, data cleaning was performed: records with missing or clearly invalid information were removed. Finally, information including job category, work location, educational requirements, years of experience, salary range, and skill keywords was extracted to construct the analysis database for this study (McKinney, 2017).

1.4.3. Data Analysis Methods

The data analysis follows a three-stage process, corresponding to different research objectives and analytical levels:

Macro-level Landscape Depiction (Descriptive Statistics): Frequency and percentage analyses were first conducted on variables such as total number of positions, geographical distribution, industry affiliation, and salary ranges. This aimed to outline the overall structure and spatial pattern of AI talent demand in the Greater Bay Area.

Meso-level Competency Deconstruction (Content Analysis and Text Mining): Employing content analysis (Krippendorff, 2003), the cleaned job description texts were coded to extract and categorize technical skill requirements (e.g., Python, TensorFlow) and comprehensive competency requirements (e.g., communication & collaboration, problem-solving). Subsequently, cross-tabulation analysis and visualization were used to reveal differences and emphases in competency demands across different cities and job types.

Micro-level Mechanisms and Policy Implications (Inductive Reasoning and Policy Analysis): The quantitative findings from the previous two stages were integrated. Combined with qualitative analysis of key policy texts such as the Guangdong Provincial New Generation Artificial Intelligence Development Plan, inductive reasoning was performed (Babbie, 2020). Finally, based on the logical chain of "Current Situation—Problems—Causes," systematic and synergistic optimization suggestions targeting educational institutions, enterprises, and policymakers were formulated.

2. LITERATURE REVIEW

2.1. Construction of an Integrated Analytical Framework

To deconstruct the underlying logic and complex causes of regional AI talent demand, this study integrates Human Capital Theory, Labor Market Supply-Demand Theory, Modern Recruitment and Matching Theory, and the Resource-Based View to construct a multi-level, logically progressive analytical framework (as shown in Figure 1). This framework aims to transcend the explanatory limitations of any single theory. By organically combining three levels—the macro-structural imbalance, micro-level corporate behavioral signals, and long-term strategic resource construction—it forms a complete causal explanatory chain, thereby revealing the economic rationality and strategic motivations behind market phenomena.

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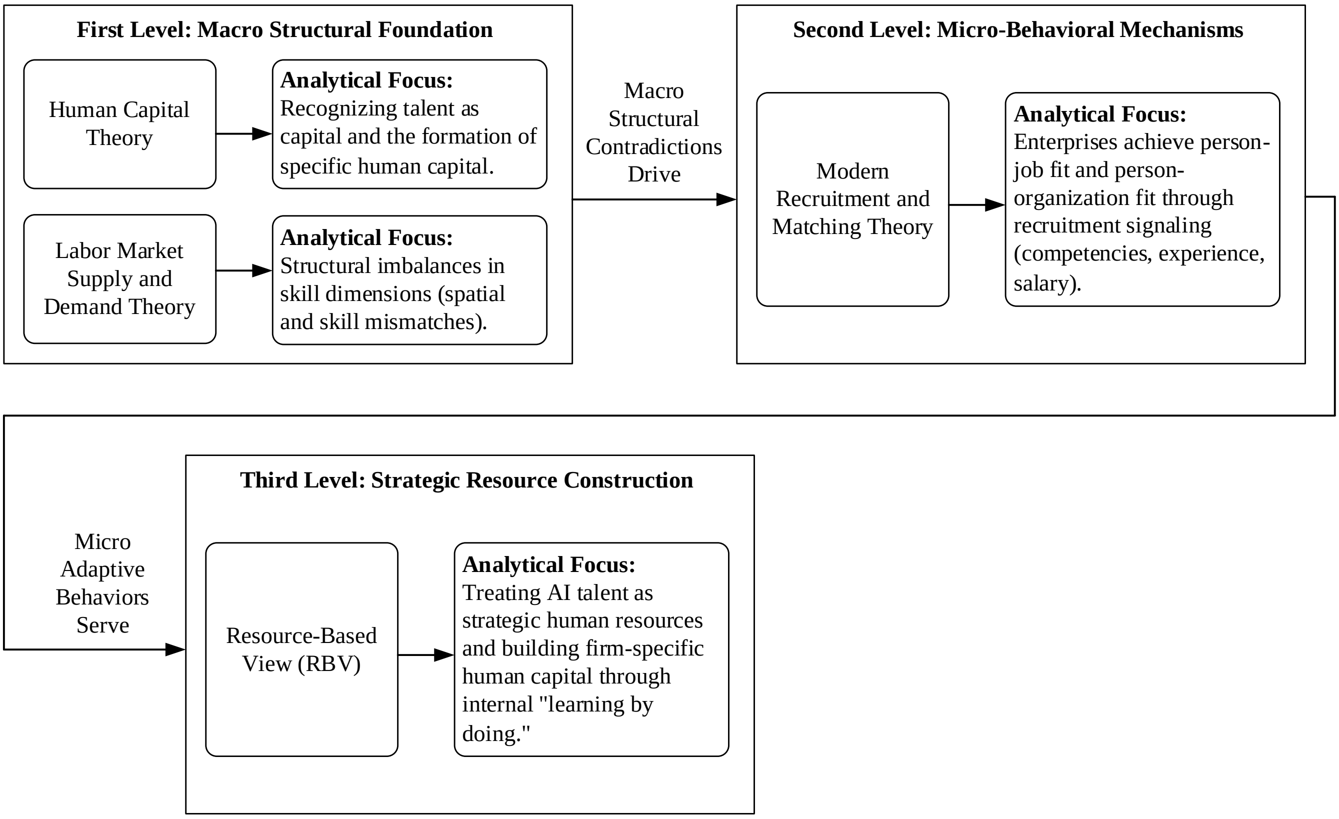

Figure 1. Multi-level Analytical Framework for AI Talent Demand

Level 1: Macro-structural Foundation — Human Capital as Scarce Capital and Market Mismatch

The starting point of this framework is the view of AI talent as a critical factor of production. Human Capital Theory (Becker, 1994) provides the core perspective, defining the AI knowledge and skills that individuals acquire through education and training as a form of "specific human capital" capable of generating future economic returns. The high salary competition among firms for such talent effectively acts as market pricing for its scarcity and high productivity. However, this demand is not uniformly met. Labor Market Supply-Demand Theory suggests that "skill mismatch" is common in technology-intensive fields, where the pace of industrial iteration outstrips the adjustment capacity of the education system's supply (Autor, 2015). This study employs this perspective to analyze the disequilibrium and economic implications of AI talent demand within the Greater Bay Area, considering both spatial agglomeration and skill dimensions.

Level 2: Micro-behavioral Mechanism — Corporate Signaling and Screening Strategies

The macro-structural contradictions directly drive firms' micro-level recruitment practices. Modern Recruitment and Matching Theory conceptualizes recruitment as a strategic process through which firms proactively send signals to the labor market to identify suitable talent (Rynes & Cable, 2003). Specific skill requirements, experience preferences, and salary ranges within job descriptions serve as crucial signals conveying the type of human capital sought by the firm (Spence, 1973). In this process, firms seek not only a "person-job fit" but also highly value a "person-organization fit," which involves assessing whether candidates possess the "complementary skills" essential for adapting to a rapidly changing environment, such as learning agility and collaboration skills (Kristof-Brown et al., 2005). Leveraging this theory, this study decodes how firms adjust these "capability signals" to cope with macro-level supply shortages through an in-depth analysis of job advertisement texts.

Level 3: Strategic Resource Construction — From Talent Competition to Organizational Capability Accumulation

The ultimate goal of firms' micro-level recruitment behavior is to build sustainable competitive advantages. The Resource-Based View offers an ultimate strategic-level explanation for this phenomenon (Barney, 1991). This theory posits that resources characterized by value, rarity, inimitability, and non-substitutability are the source of a firm's sustained competitive advantage. In the knowledge economy era, a team equipped with advanced AI skills and composite competencies constitutes a critical strategic human resource (Ployhart, 2006). Consequently, the competition for AI talent transcends the traditional domain of human resource management and evolves into a key battle for firms to acquire and accumulate core strategic resources. This underscores why many firms, particularly those in the manufacturing-rich Greater Bay Area, recruit recent graduates on a large scale and cultivate them systematically. This approach constitutes a strategic investment aimed at forming firm-specific human capital through internal "learning-by-doing," which is challenging for competitors to replicate, thereby creating long-term competitive barriers (Becker, 1994).

2.2. The Chinese Path and Guangdong's Distinctive Characteristics within the Global Wave

In the global paradigm shift of the AI industry from "perceptual intelligence" to "cognitive intelligence," technological breakthroughs such as Large Language Models and Generative AI are driving a new wave of application innovation and industrial restructuring (Brynjolfsson & McAfee, 2017). Within this global wave, China has elevated AI to a national strategic level and, through industrial policy guidance, has formed an overarching pattern where the three major agglomeration regions—Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Greater Bay

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Area—serve as three pillars (Li & Wang, 2017). Among these, Guangdong Province's development path is unique: its core advantage relies not solely on fundamental algorithmic innovation but more on a robust capacity for deep "technology-industry" integration and engineering implementation, catalyzed by its strong manufacturing foundation and highly dynamic market ecosystem (Guangdong Provincial People's Government, 2025; Department of Science and Technology of Guangdong Province, 2023).

At the policy level, the Guangdong Provincial New Generation Artificial Intelligence Development Plan clearly emphasizes "empowering the real economy." In terms of the industrial ecosystem, a distinct functional division has emerged: Shenzhen focuses on frontier technology and rapid industrialization, Guangzhou emphasizes comprehensive R&D and frontier exploration, while Foshan and Dongguan serve as testbeds for large-scale manufacturing applications (Zhang & Ruan, 2024; Department of Science and Technology of Guangdong Province, 2023). Notably, the generational technological leap represented by large models is quickly reshaping the regional human capital demand map—traditional skills are under pressure of depreciation, while demands for emerging engineering capabilities such as "Prompt Engineering," "model fine-tuning," and "AI solution architecture" are growing sharply (World Economic Forum, 2023). This distinctive regional industrial context and technological dynamic provides a crucial real-world scenario and analytical entry point for this study to deeply analyze how technological iteration differentially shapes the structure of local labor markets.

2.3. Structural Imbalance in AI Talent Supply and Demand and Its Multi-dimensional Manifestations

Globally, the supply and demand for AI talent exhibit a pronounced structural contradiction. At its core is a systematic mismatch between the pace, structure, and quality of human capital supply and the rapidly evolving needs of the industry (Acemoglu & Restrepo, 2018). In the Chinese context, this contradiction specifically manifests as an imbalanced state of "triple overlap." First, there is an imbalance in hierarchical structure, characterized by a severe scarcity of top-tier R&D talent in frontier "hard-tech" fields, such as fundamental algorithms and chip design, alongside a critical shortage of engineering implementation and versatile application talent capable of translating AI technologies into practice (Ministry of Industry and Information Technology of the People’s Republic of China, 2017). Second, there exists a fracture in skill structure, where the education system's training tends to prioritize algorithmic theory and general knowledge, while the industry urgently requires versatile talent equipped with engineering methodological capabilities (e.g., MLOps and system architecture), specific domain knowledge, and business acumen (Guo & Shen, 2024). Third, a spatial agglomeration of talent demand is evident, with a high concentration in first-tier cities and core industrial clusters, which triggers a strong "siphoning effect" exacerbating regional development disparities (Chen et al., 2022).

Further research indicates that the net effect of AI on employment lies in creating complementary roles (Autor, 2015). While automating repetitive tasks, AI significantly elevates the demand for "human-exclusive complementary skills" such as advanced analysis, creative problem-solving, human-machine collaboration, and ethical judgment. This signifies a fundamental evolution in the composition of talent capabilities in the AI era: technical proficiency is merely the "entry ticket," while long-term value and irreplaceability are determined by soft skills and cross-disciplinary integration capabilities that are difficult for AI to replicate (Lwakatare et al., 2021).

2.4. Deconstructing the Competency Framework: From Static Maps to Dynamic Evolution

Analysis of existing literature indicates that constructing an AI competency framework has become a shared concern for both academia and industry. Scholars have proposed diverse classification systems from various perspectives. For instance, the U.S. Office of Personnel Management has issued guidelines establishing a dual-layered structure encompassing General Competencies (43 items, covering professionalism, cognitive abilities, and interpersonal collaboration) and Technical Competencies (14 items, focusing on AI and data expertise), providing a standardized reference for skills-based recruitment (Ahuja, 2024). Similarly, Li et al. (2025) propose a four-dimensional model that integrates technical application, data analysis, strategic thinking, and interpersonal interaction, further distinguishing levels such as knowledge, skills, values, and traits, reflecting in-depth consideration of competency structuring.

As understanding of the complexities of AI industrialization deepens, subsequent research increasingly emphasizes the importance of "complementary" or "meta-competencies" that extend beyond purely technical domains. The four-dimensional framework proposed by Lwakatare et al. (2021)—encompassing technical, methodological, social, and personal competencies—serves as an example. This framework explicitly points out that social competencies (e.g., collaboration) and personal competencies (e.g., learning and adaptability) are key complementary elements ensuring that technical efficacy translates into organizational and societal contexts. This view aligns with Autor's (2015) assertion regarding the increasing value of human complementary skills amid technological change.

Concurrent observations from industry further reveal the dynamic nature and emerging trend of generalization in competency demands. LinkedIn's (2023) Future of Work report distinctly categorizes AI-related skills into "AI Engineering" capabilities for professional developers and "AI Literacy" for a broader range of knowledge workers. This distinction signifies that AI competency is accelerating its transition from an exclusive asset of a few specialists to a foundational element of human capital that all practitioners should possess, reflecting the profound reshaping of the labor market's skill structure by technological diffusion.

In summary, the existing literature collectively points to a consensus: an effective framework for AI talent competency must be multi-level and multi-dimensional. It must encompass not only rapidly evolving technical hard skills and engineering methodological capabilities for implementation but also the domain integration capabilities necessary for realizing technological value, the human complementary capabilities for adapting to complex environments, and a keen attention to the increasingly essential foundational AI literacy.

3. DATA ANALYSIS AND DISCUSSION

3.1. Macro Landscape: Spatial Agglomeration of Demand and Functional Divergence of Cities

Through data collection from the "Izhanchi" platform during the autumn recruitment period in November 2024, this study obtained a total of 213 valid samples for full-time AI-related positions in

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Guangdong Province. The analysis reveals an extremely pronounced spatial disequilibrium in AI talent demand. All positions are concentrated within the nine cities of the Greater Bay Area, with no related demand observed in the 12 prefecture-level cities outside the Bay Area. This confirms the strong agglomeration effect of high-tech human capital within innovation core regions (Florida, 2002).

The distribution of demand exhibits a clear characteristic of "dual-core leadership and tiered coordination" (as shown in Table 1). Guangzhou and Shenzhen constitute the absolute dual cores of demand, collectively offering 133 positions, accounting for 62.44% of the total. Foshan and Dongguan form the second tier, contributing 13.62% and 12.21% of job demand, respectively. The combined demand of the remaining five cities is merely 11.74%. This pattern is not coincidental; it directly reflects the different roles that cities play within the regional industrial chain based on their resource endowments, illustrating the logic of regionalized allocation for heterogeneous human capital demand (Krugman, 1991).

Examining this through the lens of the Resource-Based View, the fact that Guangzhou and Shenzhen account for over 60% of postings visually demonstrates that these two cities regard high-value AI human capital as a core strategic resource for competing for future economic advantages (Barney, 1991; Chen et al., 2022). The differences in the demand structure between the dual cores of Guangzhou and Shenzhen reveal divergent human capital accumulation paths based on distinct endowments: Guangzhou leverages its higher education and research resources, tending towards investing in general human capital through the formal education system; Shenzhen, capitalizing on its mature industrial chain, focuses on cultivating firm-specific human capital through "learning-by-doing" and market mechanisms (Becker, 1994).

The demand in Foshan and Dongguan empirically supports the complementary theory within manufacturing transformation (Acemoglu & Restrepo, 2018). The core requirement of their positions is the domain integration capability of "AI technology + industrial knowledge." This indicates that the introduction of AI creates demand for new composite skills. Traditional manufacturing sectors are proactively investing in human capital for this purpose to achieve intelligent upgrading.

Table 1. City Distribution, Industrial Endowments, and Corresponding Human Capital Demand for AI Job Postings in Guangdong Province

City	Number of Job Postings	Percentage (%)	Industrial Ecosystem and Resource Endowment	Dominant Type of Human Capital Demand
Guangzhou	73	34.27%	Comprehensive S&T Innovation Hub: High concentration of universities/research institutes; Government-led digital economy pilot zones.	Diversified Composite Type: Focus on basic research, algorithm R&D (technical proficiency), and industry solution capabilities (product & commercial acumen).
Shenzhen	60	28.17%	Industrialization and Technology Center: Agglomeration of tech enterprises; Complete hardware industry chain.	Engineering and Industrialization Type: Emphasis on engineering implementation of technical proficiency and domain integration capabilities of AI with hardware/communication.
Foshan	29	13.62%	Traditional Manufacturing Hub: Strong foundation in home appliances, equipment manufacturing.	Deep Application and Integration Type: Core focus is on domain integration capability (industrial knowledge + AI) and specific technical application skills (e.g., computer vision).
Dongguan	26	12.21%	Global Electronics Manufacturing Base: Complete consumer electronics industry chain.	Scenario-based and Operation/Maintenance Type: Focus on the implementation and operational maintenance of AI within electronic manufacturing processes.
Other Cities	25	11.74%	Specialized industries or specific applications.	Basic Application Type: Initial emergence of demand for foundational AI literacy, marking the onset of the diffusion of AI skills as general human capital.

3.2. Micro-Perspective: Job Structure, Experience Preference, and Market Pricing

3.2.1. Concentration of Job Demand: Highlighting the Structural Shortage of Engineering Capability

Analysis of job functions reveals a highly concentrated market characteristic (as shown in Table 2). Demand for "Algorithm Engineers" is overwhelmingly dominant (163 job postings, 76.53%), while demand for positions in specialized sub-fields like Natural Language Processing is zero. This highly generalized job label profoundly indicates that the industry is in a critical transition phase from R&D innovation to engineering implementation. What the market desperately lacks is not algorithm researchers, but rather engineering talent capable of transforming algorithmic models into stable, deployable products. This exposes the mismatch between the supply side (universities cultivating talent with general theory) and the demand side (the industry requiring engineering methodological capabilities) in terms of skill dimensions—namely, an insufficient supply of effective engineering-oriented human capital.

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Table 2. Demand Distribution of AI Specialized Job Categories

AI Job Category	Number of Job Postings	Percentage (%)
Algorithm Engineer	163	76.53%
Deep Learning	21	9.86%
Machine Learning	16	7.51%
Machine Vision	10	4.69%
Natural Language Processing	0	0.00%

3.2.2. Pronounced Preference for Recent Graduates: Long-term Human Capital Investment Strategy

Corporate requirements for work experience in AI talent show a significant "youth-oriented" tendency (as shown in Table 3). The data indicate that demand for recent graduates is most prominent (112 positions, accounting for 52.58%), far exceeding the demand for experienced professionals with over three years of experience (7.98%). This phenomenon challenges the traditional perception that high-tech industries generally prefer experienced "battle-ready" talent.

Table 3. Distribution of Corporate Requirements for AI Talent Work Experience

Work Experience	Count	Percentage (%)
Recent Graduate	112	52.58%
1 Year Experience	40	18.78%
2 Years Experience	13	6.10%
3+ Years Experience	17	7.98%

From the perspective of the Resource-Based View, large-scale recruitment of recent graduates can be seen as a long-term strategic investment by firms to build difficult-to-imitate core competitiveness. Through organizational cultural immersion, training in proprietary technical systems, and practical business experience, firms can gradually transform general human capital into firm-specific human capital deeply embedded within the organization, thereby securing sustained and stable long-term returns (Ployhart, 2006). Especially in an environment of rapid technological iteration, this strategy reflects firms' emphasis on "meta-competencies" such as learning ability, adaptability, and problem-solving potential, whose value surpasses that of specific existing skills that may quickly become obsolete (Autor, 2015).

Furthermore, the external policy environment reinforces this tendency. Taking Guangdong Province and major cities like Guangzhou and Shenzhen as examples, their employment promotion policies explicitly expand the scope of "recent graduates" to include job seekers within two years of graduation and have introduced a series of measures centered on "creating jobs, enhancing skills, optimizing services, and strengthening safeguards." On one hand, the policies focus on developing jobs related to new quality productive forces like AI (Guangdong Provincial Employment Promotion and Labor Protection Leading Group, 2025). On the other hand, by providing financial incentives such as social insurance subsidies, employment subsidies of up to 10,000 yuan, and 3,000-yuan entrepreneurship and job-seeking subsidies to small and micro enterprises hiring recent graduates, they reduce corporate labor costs (Human Resources and Social Security Department of Guangdong Province, 2025). Within this framework, the roles of government and enterprises are clearly delineated: the government acts as policy maker, service provider, and regulator, using tools like subsidies to incentivize enterprises and protect labor rights; enterprises act as job creators and policy respondents, encouraged to expand recruitment scale and participate in university-industry collaboration. This policy synergy further explains the structural reasons for the strong corporate demand for recent graduates.

In summary, corporate preference for recent graduates stems not only from strategic considerations for long-term human capital accumulation but also resonates with active local government employment promotion policies, jointly shaping the significant characteristic of "youth-oriented" experience demand in the current AI talent market.

3.2.3. Educational Requirements and Salary Distribution: Market Pragmatic Logic and Skill Premium Mechanism

Corporate educational requirements for AI talent are highly concentrated on applied degrees. The data show that the combined demand for bachelor's (46.48%) and associate's (40.38%) degrees reaches 86.86%, while demand for master's degrees and above accounts for only 5.63%. This distribution pattern clearly indicates that in the market's engineering implementation and scaling stage, the traditional "academic diploma" as a single signal of capability is weakening. According to Signaling Theory (Spence, 1973), firms are shifting towards a more complex signaling system that relies on "project experience," "internship achievements," and "technical portfolios," which can directly indicate practical competence and rapid learning potential, in order to screen for suitable talent more efficiently.

Simultaneously, the salary distribution structure is highly consistent with the aforementioned educational requirements. Salaries are generally concentrated in the mid-range of 4,000 to 10,000 yuan per month (as shown in Figure 2), reflecting the market's equilibrium pricing for junior, application-oriented human capital, primarily composed of recent bachelor's and associate's degree graduates, in line with the basic principles of labor market supply and demand theory (Autor, 2015).

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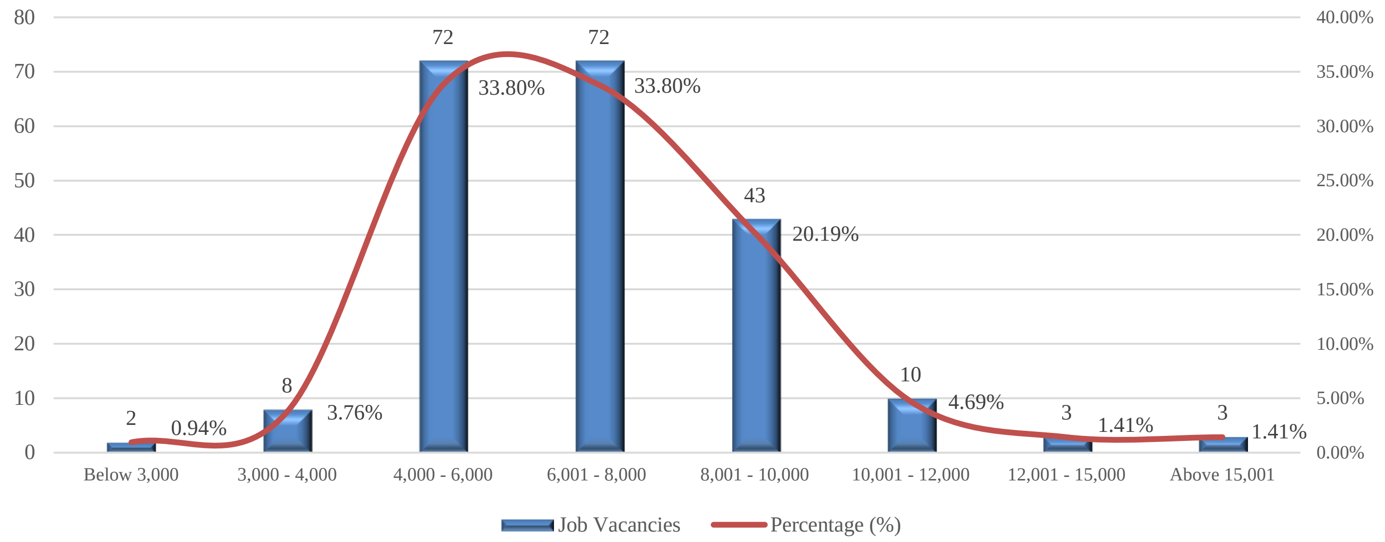

Figure 2. Salary Distribution in the AI Industry of Guangdong Province

However, significant variations within this salary range reveal a deeper market pricing logic—the skill premium mechanism. Analysis shows that the marginal return on merely mastering foundational instrumental skills like Python and general machine learning frameworks is narrowing. Conversely, it is the composite talent capable of combining core technical hard skills with domain knowledge integration capabilities (e.g., finance, healthcare), product and commercial acumen, or complex human-machine interaction design abilities who can secure compensation significantly above the market median. This confirms that the modern labor market possesses a refined ability to identify and differentially price heterogeneous human capital (Zolas et al., 2020).

3.3. Competency Framework: A Multidimensional Analysis of Recruitment Texts

Based on the analysis of job description texts, this study reveals the multidimensional competency framework currently demanded by the market for AI talent and its regional characteristics. Specifically, a clear hierarchical structure is presented: technical proficiency represented by Python (mentioned in 92% of postings), TensorFlow/PyTorch (85%), and Data Structures & Algorithms (78%) has become the basic entry-level configuration. Over 60% of engineering positions emphasize keywords related to MLOps, such as "model deployment," "operation and maintenance," and "system architecture design," highlighting the core status of engineering and methodological capabilities. In manufacturing hubs like Foshan and Dongguan, job descriptions frequently include requirements such as "familiar with production processes," "understand process defects," and "industry background preferred," confirming the rigid demand for domain integration capability in specific scenarios.

Simultaneously, complementary human capabilities such as "communication & collaboration," "problem-solving ability," "learning ability," and "innovative thinking" are mentioned in over 70% of positions. Their frequency of mention shows a positive correlation with salary ranges, reflecting the market premium for high-order cognitive and social skills. Furthermore, a few non-technical positions have begun to include requirements like "understand basic AI principles" and "able to use AI tools to enhance efficiency," indicating that foundational AI literacy is gradually diffusing into a broader range of functional areas.

In summary, AI talent demand in Guangdong Province exhibits, at the macro level, high agglomeration and a tiered division of labor, while at the micro level, it shows a strong preference for "young, application-oriented talent with engineering implementation potential and high learning resilience." The concurrent dilemma of "recruitment difficulties" and "employment difficulties" essentially stems from the industry's urgent need, during the engineering implementation phase, for a large volume of versatile applied human capital that integrates technology, engineering, and domain knowledge in a three-dimensional manner. The existing education supply and market screening mechanisms have not yet effectively responded to this structural shift.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1. Conclusions

This study reveals that the demand for AI talent in Guangdong Province is a multidimensional phenomenon with a clear structure and deep-seated drivers. The findings indicate that, in terms of spatial patterns, talent demand is highly concentrated within the Guangdong-Hong Kong-Macao Greater Bay Area, forming a tiered division of labor characterized by "Guangzhou and Shenzhen as sources of innovation—Foshan and Dongguan as hubs for integrated application." This reflects the agglomeration effects described in New Economic Geography and is a direct outcome of regional resource endowments and differentiated industrial functions.

Regarding supply-demand dynamics, the core of the structural contradiction lies in the insufficient effective supply of "engineering-oriented and application-type human capital." The market urgently requires versatile talent capable of solving complex implementation problems, not merely graduates equipped with theories and algorithms. Correspondingly, in terms of market behavior, enterprises engage in long-cycle strategic investments aimed at building firm-specific human capital through recruitment strategies that "prefer recent graduates but emphasize project experience," alongside pragmatic educational-salary positioning. They also dynamically reshape their competency screening signals to address current supply bottlenecks.

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In the composition of competencies, the study empirically supports a multidimensional framework encompassing technical proficiency, methodological capability, domain integration capability, human complementary capabilities, and foundational AI literacy. Among these, engineering methodology and specific domain knowledge hold critical importance in Guangdong, particularly within manufacturing contexts. These findings collectively lead to the conclusion that the current supply-demand imbalance in the talent market is, in essence, a systematic mismatch between the needs of industrial practice and the existing talent supply system at the structural, competency, and signaling levels.

In terms of theoretical contributions, first, this study offers a reinterpretation of the Resource-Based View within a regional industrial context. It finds that, within a manufacturing-driven regional innovation system, the most strategically valuable human resources are not necessarily external "plug-and-play" experts, but rather adaptable young engineering teams who can be gradually internalized as firm-specific assets through large-scale recruitment and internal "learning-by-doing" mechanisms. This deepens the theoretical understanding of the strategic path for constructing human capital reserves through sustained internal investment.

Second, it constructs a "structure-signal" analytical framework. The study incorporates macro-level structural contradictions (spatial agglomeration, supply-demand mismatch, competency fractures) and micro-level market signal evolution (reshaping of corporate recruitment standards, dynamic salary pricing) into a unified framework for dynamic analysis. This approach helps bridge the common disconnect between macro and micro perspectives found in previous research.

Finally, it achieves empirical validation and contextual extension of the AI talent competency framework. The study not only empirically validates the existence of a multidimensional competency model but also clarifies the pivotal role of "engineering methodological capability" in industrialization, highlights the importance of "domain integration capability" in the intelligent transformation of manufacturing, and captures the emerging trend of "foundational AI literacy" permeating non-technical roles. This provides new evidence for understanding technological diffusion and skill structure transformation.

4.2. Recommendations

4.2.1. For Higher Education and Vocational Education: From Knowledge Transmission to Capability Co-creation

Based on this study, the following reform recommendations are proposed for higher education and vocational education. The core of these recommendations lies in promoting a strategic transformation of institutions from traditional "knowledge transmitters" into "human capital co-creators."

Concretely, the curriculum system requires innovation. The implementation of a "Dynamic Modular" and "Full-Chain Project-Based" approach is recommended, with industry experts jointly participating in designing practical projects based on real-world scenarios. This will allow students to fully experience the entire engineering lifecycle, from requirements analysis to model deployment.

In terms of faculty development, a "Two-Way Revolving Door" system should be established. This system would encourage faculty to serve as "In-Plant Research Fellows" in enterprises to update their industrial understanding, while concurrently recruiting senior corporate engineers to serve as "Practitioner Professors."

Furthermore, the assessment mechanism needs fundamental reform. A diversified evaluation system centered around verifiable "Capability Credentials" should be constructed. Substantive contributions recognized by enterprises, such as project outcomes and internship performance, should be converted into official academic credits or authoritative micro-credentials.

These reforms aim to align closely with the industry's structural demand for engineering-oriented and versatile talent, achieving dynamic synergy between educational supply and market needs.

4.2.2. For Enterprises: From Talent Competition to Ecosystem Co-construction

This research indicates that enterprises should move beyond a zero-sum "talent war" mindset and transition towards an ecosystem co-construction strategy based on long-term investment and collaborative development.

Specifically, enterprises can proactively engage in early-stage talent cultivation through a Preemptive Recruitment Strategy. Examples include co-establishing "Specialized Training Classes" or "Joint Laboratories" with universities or launching "Innovation Challenges," thereby identifying and attracting potential talent during their formative stages.

Regarding Internal Empowerment, enterprises should design "Foundation Strengthening Programs" for new hires. Integrating training, mentorship systems, and rotational job practice can transform short-term training costs into long-term strategic investments for building firm-specific human capital.

Concurrently, it is essential to deepen Industry-University-Research collaboration. Enterprises should actively open up real-world application scenarios and mid-to-long-term technical challenges to universities and research institutions. This approach serves not only to absorb external intelligence but also to cultivate and incubate future talent.

These measures collectively point towards a core transformation: enterprises should evolve from being passive consumers of talent into proactive developers of human capital and co-builders of the innovation ecosystem.

4.2.3. For Government and Industry Associations: Serving as System Architects and Market Facilitators

This study suggests that government and industry associations should transcend traditional regulatory roles and proactively assume the functions of "System Architects" and "Market Facilitators." Their focus should be on constructing an institutional environment and public platforms that reduce transaction costs and enhance the efficiency of human capital matching.

Concretely, they should first provide precise data public services. By integrating multi-source data, they can regularly release authoritative reports, such as the Analysis Report on AI Talent Demand and Competencies in the Guangdong-Hong Kong-Macao Greater Bay Area, forming a dynamically updated "Regional Human Capital Development Map" to inform decision-making for all stakeholders.

Secondly, they need to design and implement incentive-compatible policy tools. Examples include launching "Industry-Education Integration Performance Packages" that offer substantial incentives

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like tax benefits or enhanced R&D expense deductions to enterprises deeply engaged in university-industry collaboration. Concurrently, preferential resource allocation can be directed towards universities demonstrating significant collaborative outcomes.

Finally, they should lead the co-development of skill standards and a credit system. In collaboration with leading enterprises, industry associations, and universities, they can jointly develop skill certification standards for in-demand roles like "AI Application Engineer." Furthermore, linking certification results with policies such as talent settlement and professional title evaluation will help establish a regionally recognized, credible "Skill Credit" system.

These initiatives aim to correct structural failures in human capital investment, signaling, and resource allocation within the market through institutional innovation and platform construction.

4.3. Research Limitations and Future Outlook

Beyond its conclusions and contributions, this study has certain limitations, which simultaneously point to directions for future research.

The primary data source for this study was a single recruitment platform. Although representative to a certain extent at the regional level, it does not encompass other recruitment channels such as headhunters or internal referrals, which may affect the comprehensive portrayal of demand. Secondly, the study employed cross-sectional data from November 2024, which effectively captures concentrated demand during a peak recruitment period but cannot reflect the seasonal fluctuations and long-term evolutionary trends of talent demand. Furthermore, the current analysis is primarily based on job advertisement texts, representing a typical "demand-side" unidirectional perspective. It does not integrate feedback from job seekers (the supply side) or post-hire actual performance data, thus limiting its ability to reveal the complete person-job matching mechanism.

Based on the aforementioned limitations, future research could deepen exploration in the following directions: Methodologically, a mixed-methods research design could be adopted, combining recruitment data analysis, and in-depth interviews with HR managers and business leaders, and follow-up surveys of graduates for triangulation. This would provide a more comprehensive understanding of the internal logic of talent screening and matching. In terms of research topics, there is an urgent need for longitudinal tracking studies to empirically examine the dynamic impact of generational technological leaps, such as large models, on job structures, skill demands, and compensation systems. Simultaneously, cross-regional comparative studies (e.g., comparing the Guangdong-Hong Kong-Macao Greater Bay Area, the Yangtze River Delta, and the Beijing-Tianjin-Hebei region) could be conducted to deeply analyze how different regional industrial "genes" (e.g., manufacturing-led, finance-driven, or R&D-intensive) differentially shape the ecology of AI talent demand. This would provide solid theoretical support for the nation in formulating differentiated regional talent and industrial policies.

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