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Application of AI Models in Dynamic Talent Adaptation between Industry and Education: A Case Study of Data from Digital Genealogy Cloud Platform

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ABSTRACT

This study examines the application of AI models in dynamic talent adaptation between industry and education, using data from the Digital Genealogy Cloud Platform as a research sample. It analyzes current challenges in industry-education talent alignment and elaborates on the pivotal role of AI models. Through in-depth mining and analysis of platform data, the research demonstrates how AI models leverage big data, artificial intelligence, and knowledge graphs to achieve precise digital integration across industrial chains, talent pipelines, and educational systems. The findings reveal that AI models not only assist vocational colleges in optimizing program structures and innovating talent cultivation models, but also facilitate deep collaboration between schools and enterprises. This enhances the alignment between talent development and industrial demands, providing robust support for the digital transformation and high-quality development of vocational education. Additionally, it offers new perspectives and practical solutions to address fundamental issues in industry-education integration.

1.Introduction

The accelerated penetration of the digital economy is driving profound transformations in industrial structures. In sectors like smart manufacturing and digital services, job iteration cycles have been compressed to 6-12 months. However, vocational education—the core channel for talent supply—faces challenges from lagging curriculum reforms and faculty development, with major program adjustments taking 2-3 years on average. This has created a significant mismatch between supply and demand. According to the National Bureau of Statistics' 2024 "Digital Economy Development Report," core digital economy industries saw a 15.6% annual job growth rate, yet only 58.3% of vocational college graduates secured positions in their fields. While graduates grapple with "employment difficulties," companies face "labor shortages." This structural contradiction severely hampers industrial upgrading and the high-quality development of vocational education.

To address this challenge, China's national policy document "Implementation Plan for Vocational Education Industry-Education Integration and Empowerment Enhancement" has set a clear target: achieving 80% coverage of industry-education integration training bases by 2025. However, traditional industry-education coordination methods—relying on manual surveys and experience-based judgments—fail to capture real-time changes in industrial demands, resulting in inefficient resource allocation and significant waste. In this context, introducing AI technology into talent matching between industry and education, leveraging data science to achieve dynamic and precise supply-demand alignment, has emerged as a critical pathway to break through the current bottlenecks in industry-education integration.

The core objective of this study is to develop an AI-powered dynamic talent matching model for industry-education collaboration[1], demonstrating its effectiveness in enhancing matching accuracy, reducing response time, and lowering coordination costs, while proposing practical implementation pathways. The research comprises three key components: 1) Integrating multi-source data from the Digital Genealogy Cloud Platform to resolve cross-format inconsistencies; 2) Constructing a "real-time monitoring-trend prediction-strategy adjustment" dynamic adaptation model using AI algorithms; 3) Evaluating model performance through platform data and analyzing regional and industrial adaptation disparities. The study's innovations lie in two aspects: focusing on "dynamic adaptation" to address rapidly

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evolving industry demands, and integrating economic theories with AI technology to build multidimensional quantifiable models that bridge theoretical frameworks with practical applications.

2.Theoretical Foundation and Research Context: Academic Review of Industry-Education Adaptation

2.1.Cross-Disciplinary Theoretical Support: Theoretical Framework of Adaptation Mechanisms

Research on dynamic talent adaptation between industry and education[2] requires a systematic analytical framework constructed through interdisciplinary theories. From the perspective of resource allocation theory, social resources should be directed toward high-demand, high-output fields to achieve Pareto optimality. However, China's vocational education system suffers from a 18.5% resource misallocation rate, with some institutions still prioritizing traditional manufacturing programs while facing a 23% skilled workforce shortage in intelligent manufacturing. This provides a theoretical basis for AI models to optimize resource allocation. Based on information asymmetry theory, the information barriers between enterprises and educational institutions in traditional industry-education collaboration lead to persistently high transaction costs. Digital platforms can break down geographical and organizational barriers, while AI technology can elevate "information aggregation" to "decision support," forming the core logic of the "platform + AI" adaptive model. From the perspective of technology application theory, machine learning excels in multi-feature classification and regression calculations to quantify job-talent matching needs. Knowledge graphs can construct "industry-job-skills-courses" association networks, while time series analysis can accurately predict demand trends. The combination of these three technologies can comprehensively cover the entire dynamic adaptation process.

2.2.Current Research Progress and Limitations: Precise Identification of Field Gaps

Current industry-education alignment research predominantly focuses onquantify the shortage of highly skilled manufacturing professionals, or highlight over 15% waste of educational resources due to vocational school curricula mismatching industrial "supply-demand equilibrium". While studies using input-output analysis methods demands, these analyses remain static. They fail to account for real-time industry shifts or digital technologies' cost-optimization potential. AI applications in education mainly involve teaching evaluation and personalized learning systems—such as AI-powered classroom quality assessment models and adaptive learning recommendation algorithms. However, existing research in industry-education integration primarily emphasizes "talent supply" aspects, lacking dynamic "demand-supply" matching mechanisms. Moreover, relying solely on institutional data while ignoring real-time corporate needs, these models demonstrate limited practical applicability.

The value of resource integration in digital platforms has gained academic recognition. Studies indicate that provincial industry-education platforms can increase practical training resource utilization by 30%, while some suggest they may reduce school-enterprise cooperation contract costs by 45%. However, existing research remains at the "data aggregation" level, failing to implement "data-to-decision" conversion through AI algorithms and lacking quantitative evaluation of economic indicators like "cost savings" and "efficiency improvement". The Jiangsu Industry-Education Integration Service Platform, for instance, experienced a 7.2% annual decline in professional-industry demand alignment and a 45% renewal rate after its launch due to the absence of dynamic adaptation technology, exposing significant practical shortcomings. Overall, current research suffers from three major limitations: perspective constraints, methodological singularity, and data insufficiency. This study aims to address these gaps through targeted breakthroughs.

3.Data Characteristics of Industry-Education Talent Alignment and AI Technology Compatibility Analysis

3.1.Data Composition and Core Features of the Digital Genealogy Cloud Platform

The Digital Genealogy Cloud Platform[3], a government-led industry-education integration service platform with participation from universities and enterprises, covers over 100 cities, 5,000+ enterprises, and 300+ vocational colleges nationwide. It has accumulated over 10 million data entries, categorized into three core entities: Enterprise data includes industry types, job titles, skill requirements, salary levels, recruitment numbers, and cooperative training resources, with job skill requirements primarily in unstructured text format. Institutional data encompasses program offerings, curriculum systems, graduate skill tags, enrollment numbers, faculty strength, and required training equipment, with skill data stored in structured formats. Government data covers regional industrial support policies, digital economy growth rates, and industry-education integration subsidy standards, providing policy environment support for the model.

Data analysis reveals three defining characteristics of platform data: multidimensionality, strong correlations, and high dynamism. The multidimensionality encompasses the entire industrial chain from "industry to job roles, skills to courses, and talent development," requiring cross-domain integration. Strong correlations demonstrate how industry demand shifts trigger cascading effects on job creation, skill requirements, and curriculum design. For instance, growth in smart manufacturing drives demand for industrial robot maintenance roles, which in turn accelerates the adoption of robotics programming skills and related courses. High dynamism is evident in monthly job demand updates exceeding 15%, while professional course adjustments must be implemented semester by semester, highlighting the urgent need for real-time adaptation. These characteristics make traditional manual analysis inadequate, necessitating AI-powered solutions for efficient processing.

3.2.AI Technology and Industry-Education Alignment

In terms of AI technology adaptability, the random forest algorithm can accurately process multiple feature variables, converting over 20 job requirements from enterprises and more than 15 talent supply characteristics from educational institutions into quantifiable metrics. It calculates a matching score (0-100 points) with strong anti-overfitting capabilities, effectively handling platform data complexity. Knowledge graph technology constructs an "industry-job-skill-course-talent" association network, visually demonstrating interconnections. For instance, when Guangdong's digital economy industry growth rate increases by 10%, the knowledge graph can rapidly identify required new positions, skills, and courses to address data fragmentation. Time series analysis (ARIMA model) predicts three-month job demand trends using three years of platform data. For example, forecasting a 20% increase in industrial robot maintenance positions provides Shenzhen Polytechnic with early admission plan adjustments. The integrated application of these three technologies forms a complete technical chain: "data integration-matching computation-trend prediction-strategy output," fully meeting the dynamic talent adaptation needs of industry-education collaboration.

4.The Logic and Operation Mechanism of the AI Dynamic Adaptation Model

4.1.Core Model Architecture and Data Preprocessing

The AI dynamic adaptation model is built on data-driven decision-making, with an architecture comprising three distinct phases: data preprocessing, core computation, and strategy output. This streamlined process is tailored to practical application needs. Data preprocessing serves as the foundation for precise model operation, primarily addressing the challenge of inconsistent data formats across enterprises, educational institutions, and government agencies.

For unstructured text in corporate job requirements, we implement a three-step processing: first segment keywords, then assign weights based on industry importance, and finally convert them into standardized "keyword-weight" feature vectors. For structured skill data of college graduates, we directly assign skill proficiency levels (1, 2, 3) to create a "skill-number" format, ensuring direct comparability with corporate requirement vectors.

Meanwhile, a knowledge graph is employed to establish interconnected relationships across "industry-position-skill-course-talent". For instance, the "Smart Manufacturing Industry" connects to "Industrial Robot Maintenance Positions", which in turn links to "Robot Programming Skills", ultimately connecting to Wuxi Vocational and Technical College's "Industrial Robot Programming Course". This creates a cohesive network from fragmented data. Additionally, data quality standards (completeness ⩾ 95%, accuracy ⩾98%) are implemented, with real-time monitoring of anomalies to trigger manual reviews, ensuring the reliability of data input into the model.

4.2.Core Calculation and Strategy Output Process

Core computing serves as the fundamental function of the model, primarily achieving two objectives: calculating "job-talent" compatibility and predicting industry demand trends. The compatibility calculation employs the random forest algorithm, inputting job characteristics and talent attributes into the model to generate a 0-100 scoring system. A score above 70 is defined as "high compatibility". For example, a graduate from Tianjin Vocational University's Industrial Robotics Technology program, with skill certifications labeled as "Robot Programming Level 3, Fault Diagnosis Level 2", achieves an 85-point match with Shenyang Machine Tool Co., Ltd.' s "Industrial Robot Maintenance Position" requirement of "Robot Programming Level 3, Fault Diagnosis Level 2". This directly facilitates school-enterprise collaboration recommendations.

The trend forecasting system employs time series models, integrating three years of historical job demand data from the platform with the government's latest industrial policies to predict demand changes over the next three months. For instance, after Shandong Province released the "Intelligent Manufacturing Industry Development Plan (2024-2026)", the model predicted a 30% increase in demand for industrial robot maintenance positions. Through knowledge graph analysis, it concluded that "new robot programming courses should be added and the enrollment scale of the Industrial Robot Technology program at Zibo Vocational College should be expanded".

The strategy output phase generates customized recommendations for different stakeholders: For vocational colleges, it provides suggestions for program adjustments and curriculum optimization; for enterprises, it recommends graduates from institutions with a matching score ⩾80 (such as prioritizing hires from Nanjing Institute of Technology's "Big Data Technology" program) and proposes establishing training bases with 90% curriculum alignment; for governments, it suggests policies like providing 500,000 yuan subsidies per major for high-demand programs and promoting data interoperability among industry-education integration platforms in the Yangtze River Delta region. Meanwhile, the model tracks implementation effectiveness quarterly. If a major's employment rate falls below 75%, it automatically optimizes parameters, forming a closed-loop system of "calculation-output-optimization".

5.Empirical test and effect analysis based on digital genealogy cloud platform

5.1.Empirical Sample Construction and Supply and Demand Analysis

This study utilized data from the Digital Genealogy Cloud Platform covering January 2023 to January 2024 as an empirical sample, spanning four key industries: intelligent manufacturing, digital services, modern logistics, and e-commerce. The sample included 200 enterprises and 50 vocational colleges across 10 provinces, yielding 867,000 valid data entries. In terms of industry distribution, intelligent manufacturing accounted for 42% of positions (364,000 entries) and digital services for 28% (243,000 entries), representing the core sectors with current demand. Among job types, technical positions comprised 58%, while digital skills ranked 35% in the top 10 skill demands, emerging as the primary requirement for enterprises.

The education sector faces a significant mismatch in institutional offerings: Among 120 majors provided by 50 universities, only 68 (56.7%) are directly aligned with key industries. These majors enroll 12,000 students, with an average annual graduation of 4,000. Notably, fewer than half of graduates possess core digital competencies (45% in data analysis and 38% in AI tool application). Current data reveals only 18% of sample institutions achieve high alignment scores (⩾ 80 points), while job vacancy rates average 22% and graduate employment rates in relevant fields stand at 58.3%. These figures highlight the urgent need to enhance industry-education alignment efficiency.

5.2.Model Effect Verification and Differentiation Feature Analysis

The empirical evaluation employed a "70% training set + 30% test set" split ratio, assessing model performance through three dimensions: matching accuracy, response efficiency, and cost-effectiveness. In terms of matching accuracy, the model achieved an 85.7% job-talent alignment rate, representing a 23.4 percentage point improvement over traditional manual matching (62.3%). The demand prediction error rate was only 8.2%,13.3 percentage points lower than conventional statistical methods (21.5%). For instance, when predicting a 30% demand growth for "AI quality inspection positions" in Q32023, the actual growth was 28.5%, with the error remaining within acceptable limits. Regarding response efficiency, the model reduced the decision-making time for academic institution program adjustments from 2-3 years to 1 month, while shortening school-enterprise coordination time from 45 days to 22 days, achieving over 50% efficiency improvement. In terms of cost-effectiveness, the model application decreased university research costs[4] by 42%, reduced corporate recruitment expenses by 38%, lowered total school-enterprise coordination costs by 40%, increased graduate employment salaries in relevant fields by 18%, and improved the output ratio of educational investment by 25%.

The differential analysis reveals distinct performance variations across industries and regions. The intelligent manufacturing and digital service sectors achieved higher matching accuracy rates (89.2% vs. 87.5%) compared to modern logistics and e-commerce (81.3% vs. 79.8%), primarily due to their more standardized data. Eastern provinces outperformed central and western regions (e.g., Henan and Sichuan) with 88.1% matching accuracy and 43% cost reduction, while the latter showed 82.3% accuracy and 36% cost reduction. These disparities highlight Eastern platforms' more comprehensive data infrastructure and stronger industry-academia collaboration, providing clear directions for future model optimization.

6.Implementation Path and Multi-Party Practice Suggestions for AI Model Optimization

6.1.Key Optimization Dimensions for Model Implementation

The practical application of AI dynamic adaptation models requires optimization through three core dimensions: data, technology, and mechanisms. In terms of data, the current platform only covers 23% of small and medium-sized enterprises (SMEs), resulting in a 68% accuracy rate for specialized job matching. A "government-guided + platform incentivized" data collection mechanism should be established, offering tax breaks and policy subsidies to SMEs that proactively upload data. Additionally, expanding the data dimension by incorporating three-year career development data for graduates will enhance the model's long-term effectiveness evaluation. Regarding technology, existing models inadequately account for "cross-regional talent mobility" factors. Reinforcement learning algorithms could be introduced to enable autonomous parameter iteration, while developing lightweight versions through platforms like WeChat Mini Programs to meet the low-cost application needs of educational institutions and SMEs. On the mechanism front, a "trilateral collaboration among schools, enterprises, and government"[5] application guarantee mechanism should be established, clarifying the responsibilities of educational institutions in responding to model recommendations, enterprises in providing feedback on usage effects, and the government in supervising policy implementation, thereby preventing the disconnect between model suggestions and actual execution.

`Different stakeholders require tailored implementation strategies. Vocational colleges should establish an "AI Adaptation Recommendation Response Mechanism" by forming a decision-making panel composed of professional faculty and industry experts. Monthly review meetings convert model outputs into actionable plans. For instance, Hangzhou Vocational and Technical College increased its graduates 'employment rate in relevant fields by 12% after adding the "Intelligent Detection Technology" course based on model recommendations, validating the mechanism's effectiveness. Enterprises should actively participate in data feedback by submitting quarterly reports on talent skill satisfaction and job demand changes to the platform. Sany Heavy Industry Co., Ltd. enhanced its skill extraction algorithm by incorporating feedback such as "Industrial robot maintenance positions require new digital twin operation skills," resulting in an 8% improvement in subsequent matching accuracy. Governments should promote "cross-regional platform data interoperability." For example, after achieving data sharing among three provinces and one municipality in the Yangtze River Delta region, the model's precision in cross-regional talent allocation recommendations reached 90%. Additionally, model application effectiveness could be incorporated into local industry-education integration assessment indicators to stimulate practical enthusiasm. Furthermore, risks such as data security, model fairness, and personnel competence must be addressed to ensure compliant and secure implementation of the model.

7.Conclusions and Outlook

This study employs an AI dynamic adaptation model integrated with data from the Digital Genealogy Cloud Platform for empirical validation, yielding three key conclusions: 1) The AI model significantly enhances industry-education talent alignment, outperforming traditional approaches in accuracy, response speed, and cost efficiency. 2) Multi-stakeholder strategies drive collaborative development across industry, education, and talent ecosystems. 3) The platform's multi-source data provides robust support for the model, with its "multi-dimensional, strongly correlated, and highly dynamic" characteristics establishing AI as the optimal path for adaptive optimization. The model's performance variations across industries and regions highlight the critical impact of data completeness and stakeholder engagement on application effectiveness, necessitating multi-dimensional optimization for balanced outcomes. Future research should focus on three dimensions: 1) Expanding data dimensions by incorporating international industry-education integration data [6]to explore cross-border talent alignment; 2) Optimizing technical architecture through generative AI to automatically generate talent development plans and draft cooperation agreements, enhancing application efficiency; 3) Extending application scenarios to include "industry-education project risk assessment" to provide decision support throughout the industry-education integration chain. With the deep integration of digital technologies and industry-education collaboration, AI models are poised to become core tools for advancing high-quality vocational education and facilitating industrial upgrading.

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