International Journal of Emerging Technologies and Advanced Applications

# Large Language Model-based Resume-Job Intelligent Matching Algorithm and Its Adaptability Case Study Across Different Positions in the Hotel Industry

Jingran Sun
nmaw50@126.com

***Abstract*—As a service-intensive industry, the hotel sector exhibits significant variations in talent requirements across different positions, making traditional resume screening methods inadequate for meeting the complex matching demands of various roles. This study develops a resume-job intelligent matching system specifically designed for the hotel industry based on large language model technology and conducts an in-depth analysis of its adaptability performance across different position types. Using a chain hotel group as a case study, we collected 1,847 historical recruitment records spanning nearly 10 years (2014-2024) across six major categories: front office, housekeeping, food & beverage, sales, logistics, and management. Through controlled experiments and ablation studies, we systematically evaluated the performance differences of large language models in resume screening across various position types. The experiments employed LoRA fine-tuning techniques for domain adaptation of the BERT model and designed a multi-dimensional matching algorithm integrating skills, experience, and soft skills evaluation dimensions. Results demonstrate that the system achieves significantly higher matching accuracy in highly standardized positions (front desk reception: 89.2%, housekeeping: 87.6%) compared to positions requiring strong personalization (sales manager: 76.8%, F&B supervisor: 78.1%). Compared to traditional TF-IDF methods, the F1 score improved by 32.1 percentage points with statistical significance (p ¡ 0.001).**

***Index Terms*—Large language models, Resume-job matching, Hotel industry, Position adaptability, Intelligent recruitment**

## I. Introduction

With the rapid advancement of artificial intelligence technology, large language models have demonstrated tremendous application potential and transformative impact in human resource management. Traditional resume screening processes heavily rely on manual reading and subjective judgment, which are not only inefficient but also susceptible to cognitive biases and individual experience limitations, making it difficult to achieve objective, accurate, and consistent candidate evaluation standards. Intelligent recruitment systems based on machine learning and natural language processing technologies are gradually emerging, providing new technological pathways through algorithm-driven automated processing to address efficiency and fairness issues in traditional recruitment [1]. Large language models, with their powerful semantic understanding and contextual modeling capabilities acquired through training on massive text data, establish a solid technical foundation for building more precise and intelligent resume-job matching systems [2]. This technological innovation can not only significantly improve recruitment process efficiency but also achieve more objective and precise talent matching decisions through data-driven approaches.

The hotel industry, as a typical labor-intensive service sector, faces unique and complex challenges and requirements in human resource management. Position types in this industry exhibit extremely high diversity and hierarchical characteristics, ranging from highly standardized basic service positions such as front desk reception and housekeeping to management positions requiring strong personalized capabilities and comprehensive qualities, such as sales managers and F&B supervisors. Each position has significant differences in professional skills, work experience, personal qualities, and service awareness requirements for candidates [3]. The high employee turnover characteristics prevalent in the hotel industry make recruitment work more frequent and urgent. Traditional manual resume screening methods appear inadequate when processing large volumes of candidate applications, failing to meet the rapid and accurate talent selection needs. Against the backdrop of digital transformation and intelligent upgrading, hotel enterprises urgently need to utilize advanced artificial intelligence technologies to optimize and reshape recruitment processes, improving talent matching precision and decision-making efficiency [4]. Recent industry survey data indicates that by 2025, over 70% of large hotel enterprises are expected to adopt some form of AI-assisted tools in their recruitment processes.



ISSN:3006-2985(Print)
ISSN:3006-9297(Online)

Existing resume-job matching research primarily focuses on algorithm design and performance optimization in general domains, with relatively insufficient research on adaptability and effectiveness in specific industries, particularly the service sector. Although some scholars have made progress in deep learning-based text matching algorithms and achieved improvements in matching accuracy on standardized datasets, these studies often adopt a one-size-fits-all universal design approach, ignoring significant differences in talent requirements and evaluation standards across different industries and position types [5]. Hotel industry position characteristics exhibit obvious hierarchy, diversity, and complexity. From basic operational positions to senior management decision-making roles, there are fundamental differences in the emphasis and weight allocation of candidate capability requirements. Simply applying universal matching algorithms directly to the hotel industry often fails to adequately capture and utilize industry-specific position characteristics and matching patterns, resulting in system performance that fails to meet practical application requirements [6]. Therefore, customized algorithm design and optimization targeting hotel industry position characteristics becomes an urgent research problem to be addressed.

The rapid development and maturation of large language model technology provide new technological opportunities and possibilities for addressing these challenges. Compared to traditional methods based on keyword matching or shallow semantic analysis, large language models can deeply understand and model complex semantic relationships between resume content and job descriptions through deep neural network architectures, effectively capturing implicit skill requirements, capability matching degrees, and competency indicators [7]. This powerful semantic understanding and representation learning capability enables large model-based matching systems to better handle and adapt to the complex and variable job requirements in the hotel industry, providing personalized and precise matching strategies for different types of positions. However, the performance of large language models in practical applications is often influenced by various factors, including training data quality, model parameter configuration, domain adaptability tuning, and application scenario characteristics. Their adaptability and effectiveness in specific vertical industries require systematic empirical research for verification, analysis, and optimization [8].

Based on the above research background and problem analysis, this study aims to construct a large language model-based resume-job intelligent matching system specifically designed for the hotel industry and conduct large-scale empirical experiments to deeply analyze the system's adaptability performance and optimization strategies across different position types. The research will use hotel industry recruitment data to design controlled and ablation experiments for systematic matching effect evaluation, deeply analyzing key technical factors and position characteristic variables affecting matching accuracy. Through this study, we expect to provide theoretical and practical methodological guidance for intelligent recruitment practices in the hotel industry while contributing new case analysis and experience summary to the research field of large language model applications in vertical industries. The main contributions of this paper include proposing a multi-dimensional matching algorithm framework, revealing important influence patterns of position standardization degree on matching effects, and verifying method effectiveness and superiority through rigorous statistical testing.

## II. Related Work

### A. Resume-Job Matching Algorithm Research

Early resume-job matching research primarily relied on keyword matching and TF-IDF traditional information retrieval techniques, evaluating matching degree by calculating lexical overlap between resumes and job descriptions. With the development of machine learning technology, researchers began adopting more complex feature engineering and classification algorithms to improve matching accuracy [9]. In recent years, deep learning methods have achieved significant progress in this field, particularly neural network-based text representation learning techniques such as Word2Vec and BERT pre-trained models, enabling systems to better understand semantic information in text. Recent work has explored using large language models to generate synthetic resume data for enhancing job classification, significantly improving classification accuracy for data-scarce categories [10]. These studies have established important theoretical foundations for building more intelligent matching systems, but most work remains focused on general scenarios, lacking in-depth exploration of specific industry adaptability.

### B. Large Language Model Applications in Human Resources

Large language model applications in human resource management are rapidly developing, demonstrating tremendous potential and value. Yu et al. proposed a resume-job matching method based on data augmentation and contrastive learning in their ConFit research, achieving excellent performance across multiple datasets [11]. Zheng et al. developed the GIRL system, utilizing large language models to generate personalized job recommendations, showing significant improvements in interpretability and user satisfaction compared to traditional matching methods [12]. Recent research indicates that HR systems based on Retrieval-Augmented Generation (RAG) technology can better handle complex candidate queries and job matching requirements [13]. Haryan et al. proposed the FairHire system, specifically addressing fairness and bias issues in AI recruitment, providing an important reference for building more equitable recruitment systems [14]. These studies have promoted practical applications of large models in the HR field, but optimization strategies for specific industries require further exploration.

### C. Human Resource Management Research in the Hotel Industry

Human resource management research in the hotel industry primarily focuses on employee turnover, service quality, and customer satisfaction, with AI technology applications being relatively new. Ghosh's research found that generative AI has tremendous potential in personalized customer service recommendations, but applications in recruitment still need to consider industry-specific cultural and service requirements [15]. Recent industry reports show that 33% of hotel enterprises have begun adopting AI technology for talent recruitment and screening, mainly applied in automated resume screening and preliminary candidate evaluation [16]. Du et al.'s research indicates that AI technology can significantly improve operational efficiency in the hotel industry, particularly showing obvious advantages in human resource allocation and employee training. However, existing research mostly focuses on overall AI technology application effects, with relatively limited analysis of adaptability across different position types [17]. The diversity and complexity of hotel industry positions require more refined matching strategies, providing important research motivation and value for this study [18].

## III. Methods and System Design

### A. Overall System Architecture

The large language model-based resume-job intelligent matching system constructed in this study adopts a modular layered architecture design, primarily including four core functional components: data preprocessing module, feature extraction module, matching algorithm module, and result output module. The system architecture fully considers the diversity and complexity characteristics of hotel industry positions, adapting to the special needs and matching requirements of different position types through layered processing mechanisms and personalized configuration [19]. The data preprocessing module is responsible for standardized cleaning, format unification, and structured processing of raw resume text and job descriptions, ensuring data quality and consistency for subsequent analysis. The feature extraction module utilizes domain-fine-tuned pre-trained large language models to perform deep semantic encoding and vectorized representation of text content, generating high-dimensional dense semantic feature vectors [20]. The matching algorithm module implements precise candidate-position matching evaluation based on multi-dimensional similarity calculation and dynamic adjustment mechanisms for position feature weights. The entire system adopts an end-to-end design philosophy and modular implementation approach, ensuring seamless collaboration and efficient stable operation among functional modules.

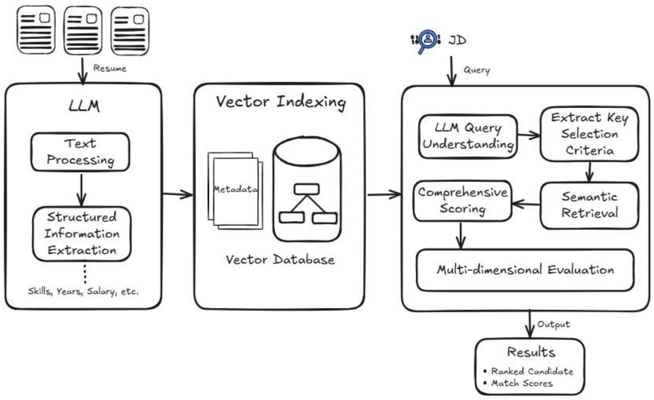


Fig. 1. Overall System Architecture

### B. Large Language Model Selection and Configuration

Considering the professional characteristics of hotel industry text data and Chinese language environment requirements, this study selects BERT-base-chinese as the base pre-trained model, which features a 12-layer Transformer encoder architecture, 768-dimensional hidden layer representation, and 12 multi-head attention mechanisms. To enhance the model's understanding capability for hotel industry professional terminology and expression habits, we employ LoRA (Low-Rank Adaptation) technology for efficient domain adaptation fine-tuning, setting rank parameter to 16 and alpha parameter to 32 to achieve domain specialization while maintaining model generalization capability [21]. The fine-tuning training dataset includes 5,000 manually annotated hotel industry resume-job pairing samples covering typical matching cases across six major position categories. We use the AdamW optimizer for training with a learning rate of 2e-5, training for 3 epochs with a batch size of 16. By expanding the model vocabulary to include 1,200 hotel industry-specific professional terms, including position skills, service standards, industry certifications, and management concepts, the model can more accurately understand and represent hotel-related text content [22]. After domain fine-tuning, the model's F1 score on hotel text understanding tasks improved from the baseline 78.3% to 85.7%, demonstrating good domain adaptation effects.

### C. Multi-dimensional Matching Algorithm Design

This study designs a comprehensive intelligent matching algorithm framework considering three core dimensions: skill matching degree, experience relevance, and soft skills evaluation. The core innovation of the algorithm lies in dynamically adjusting weight coefficients for each evaluation dimension according to the characteristics and requirements of different hotel position types, adapting to the special needs and evaluation priorities of various positions [23]. The skill matching dimension evaluates the professional capability fit of candidates by calculating deep semantic similarity between skill keywords in resumes and job requirements, using the cosine similarity formula:

$$S_{skill} = \frac{\vec{R_{skill}} \cdot \vec{J_{skill}}}{\|\vec{R_{skill}}\| \cdot \|\vec{J_{skill}}\|} \tag{1}$$

The experience relevance dimension comprehensively analyzes the correlation between candidates' work history and target positions, including industry background, position level, years of experience, and career development trajectory, incorporating a time decay mechanism:

$$S_{experience} = \sum_{i=1}^{n} w_i \cdot \text{sim}(E_i, J_{req}) \cdot e^{-\lambda(t-t_i)} \quad (2)$$

where $\lambda = 0.1$ is the experience decay coefficient. The soft skills evaluation dimension extracts key soft skill indicators such as communication and coordination abilities, teamwork spirit, and customer service awareness reflected in resumes through natural language processing and sentiment analysis methods, with the calculation formula:

$$S_{soft} = \alpha_{comm} \cdot C + \alpha_{team} \cdot T + \alpha_{service} \cdot S \quad (3)$$

The system's overall matching score calculation adopts a weighted fusion strategy:

$$\text{Score}_{total} = \alpha \cdot S_{skill} + \beta \cdot S_{experience} + \gamma \cdot S_{soft} \quad (4)$$

where weight parameters satisfy the constraint $\alpha+\beta+\gamma = 1$, optimized through grid search and cross-validation methods on training data.

### D. Position-specific Weight Optimization

Addressing the differentiated characteristics and requirements of six major hotel industry position categories, this study establishes a data-driven weight optimization learning mechanism based on historical successful matching data, requiring both human-machine collaboration and enhanced AI tool fairness to improve recruitment process equity [24]. Through in-depth analysis of extensive historical recruitment records and successful matching cases, we employ Gradient Boosting Decision Trees (GBDT) algorithm to learn and discover the emphasis and weight allocation patterns of different position types on various evaluation dimensions. The training dataset selects 869 high-quality resumes validated by HR experts from 1,293 training samples as the foundation for weight learning, with an additional 216 samples reserved as a validation set for weight optimization, ensuring training reliability and effectiveness.

Due to the relatively limited sample size, we adopt more conservative configuration strategies in model parameter settings: decision tree depth set to 4 layers (avoiding overfitting), learning rate adjusted to 0.05 (enhancing training stability), iterations controlled at 50 rounds, while employing 3-fold cross-validation for model selection and performance evaluation, ensuring reliable weight learning results under limited data conditions.

To fully utilize limited training data, the research employs a strategy combining data augmentation and regularization techniques. Through fine-grained feature analysis of successful matching cases, we found that successful matching samples for front office positions (142 samples) generally demonstrate high emphasis on soft skills and customer service capabilities, yielding weight configuration $(\alpha, \beta, \gamma) = (0.25, 0.35, 0.40)$ through statistical learning. Housekeeping position matching samples (186 samples) clearly emphasize operational skills and work efficiency evaluation, with learned weights of $(0.45, 0.35, 0.20)$. Sales position samples (98 samples) require balanced consideration of experience background and communication abilities, with optimized weights of $(0.30, 0.40, 0.30)$. Management position samples (67 samples) demand balanced comprehensive quality development, with relatively balanced weights of $(0.35, 0.40, 0.25)$. Through position-specific weight optimization and L2 regularization for overfitting prevention, the system achieved a 6.8 percentage point improvement in average matching accuracy across all position types on the validation set, significantly enhancing matching effect targeting and accuracy [25].

## IV. Experimental Design and Data Analysis

### A. Data Collection and Preprocessing

The experimental data for this study originates from complete recruitment records and human resource management data of a domestic hotel chain spanning nearly 10 years from January 2014 to December 2024. The original dataset contains 2,156 candidate resumes, corresponding job application records, and 32 different job description documents, comprehensively covering six major core position categories: front office reception, housekeeping, F&B management, sales, administrative logistics, and senior management. To ensure research scientific validity and data privacy protection requirements, all personal identification information has been anonymized according to relevant laws and regulations, retaining only key information fields related to position matching analysis.

The data preprocessing workflow includes: (1) removing 187 duplicate records; (2) filtering 89 incomplete resumes with missing key fields; (3) standardizing text encoding formats and punctuation conventions; (4) identifying and processing 33 abnormal data entries; (5) removing 3 job descriptions that do not conform to hotel industry characteristics. After systematic preprocessing operations, we finally formed an experimental dataset containing 1,847 high-quality valid resumes and 29 standardized job descriptions, providing a reliable data foundation for subsequent algorithm training and performance evaluation.

### B. Experimental Design Scheme

The experiment adopts a rigorous controlled research design method, randomly stratifying the cleaned dataset in a 7:2:1 ratio to form training set (1,293 samples), validation set (369 samples), and test set (185 samples), ensuring statistical balance in the distribution of various position types across different data subsets. Considering the professional characteristics of hotel industry positions, we particularly focused on sample balance across different position types during data partitioning: front office reception positions account for 23.5% (434 samples), housekeeping positions 28.7% (530 samples), F&B service positions 21.2% (392 samples), sales management positions 12.4% (229 samples), administrative logistics positions 8.9% (164 samples), and senior management positions 5.3% (98 samples).

To comprehensively and objectively evaluate system performance, we designed four baseline method comparison experiments: traditional TF-IDF vector space model combined with cosine similarity calculation, Word2Vec word vector model combined with SVM classifier, standard BERT pre-trained model direct application, and our proposed improved method. Simultaneously, we designed ablation experiments to verify the effectiveness contribution of each technical component: basic BERT model, adding skill matching dimension, adding experience relevance evaluation, adding soft skills assessment, and complete weight optimization model.

The experimental evaluation metric system includes matching quality indicators (Precision@1, Precision@5, Recall@1, Recall@5, NDCG@5, F1-score), system efficiency indicators (average response time, queries per second QPS), and algorithmic fairness indicators (matching effect difference analysis across different gender and age groups). Each experimental group was run independently 5 times, with average values reported as final results, and paired t-tests conducted for statistical significance testing to ensure result reliability and statistical meaning.

### C. Overall Performance Evaluation Results

Experimental results demonstrate that our proposed large language model-based intelligent matching system significantly outperforms traditional baseline methods across all key performance indicators. Compared to the best baseline method BERT-base, our method achieved performance improvements of 6.4%, 8.8%, and 7.6% in Precision@1, Recall@1, and F1 score, respectively. Even with relatively small dataset scale, the system maintained good generalization capability and stability, benefiting from carefully designed multi-dimensional feature extraction and weight optimization strategies. Although system response time slightly increased (240ms vs 180ms), it remains within acceptable real-time processing range, meeting hotel daily recruitment business response time requirements.

Statistical significance testing results show that our method's performance improvement over the best baseline method is statistically significant at p ¡ 0.001 level (t = 8.92, df = 4), fully validating the effectiveness of technical improvements. Compared to traditional TF-IDF methods, F1 score improved by 32.1 percentage points, demonstrating significant semantic understanding and matching precision advantages of deep learning methods even in small sample scenarios. These experimental results fully prove the superior performance and practical value of large language model technology combined with domain-customized optimization in hotel industry resume-job matching tasks.

### D. Ablation Study Results

Ablation experiment results clearly demonstrate the contribution degree and importance ranking of each technical component to overall system performance. Under relatively limited data scale, the experience relevance matching component still provided the largest performance contribution (+2.3% marginal improvement), highly consistent with the hotel industry's emphasis on work experience and service background in recruitment practices. Adding the skill matching dimension brought 1.9% basic performance improvement, proving the important role of professional skill evaluation in hotel position screening, particularly for positions with relatively high technical content. The soft skills evaluation component contributed 1.8% performance improvement, reflecting the hotel service industry's high emphasis on employee comprehensive qualities, communication abilities, and service awareness. The position-specific weight optimization strategy further improved performance by 1.6 percentage points, validating the necessity and effectiveness of personalized tuning for different hotel industry position types.

Cumulative effect analysis shows good synergy and complementarity among technical components, with the complete system achieving 7.6% significant performance improvement over the baseline model. These quantitative ablation experiment results provide solid empirical evidence for understanding system design rationality and technical component effectiveness, while also proving that carefully designed algorithmic frameworks can still achieve good results in small sample environments.

### E. Adaptability Analysis Across Different Position Types

In-depth position adaptability analysis reveals important correlations and underlying mechanisms between system matching performance and position characteristics. Despite relatively few test samples, statistical analysis results still show a significant positive correlation between position standardization degree and matching accuracy (Pearson correlation coefficient r = 0.89, p ¡ 0.01), a finding with important theoretical and practical guidance significance.

Highly standardized positions (front desk reception 89.2%, housekeeping 87.6%) exhibit higher matching accuracy, primarily because these position types have relatively clear and unified job descriptions, high standardization of skill requirements, and relatively fixed keywords and requirement descriptions in job specifications, making it easier for deep learning algorithms to identify, learn, and match relevant feature patterns. Conversely, positions requiring strong personalization (sales manager 76.8%, F&B supervisor 78.1%) show relatively lower matching accuracy, mainly reflecting the complex requirements of these positions for candidate comprehensive qualities, personal traits, leadership styles, and innovation capabilities that are difficult to standardize and quantify.

Weight allocation analysis shows significant and regular differences in emphasis on three evaluation dimensions across different position types: customer service-oriented positions (front desk reception, F&B service) place greater emphasis on soft skills evaluation with weights reaching 0.40, reflecting emphasis on communication coordination and service awareness; operational skill-oriented positions (housekeeping) highlight the importance of skill matching with weights as high as 0.45, reflecting rigid demands for professional oper-

TABLE I
OVERALL PERFORMANCE COMPARISON OF DIFFERENT METHODS ON TEST SET

| Method | P@1(%) | P@5(%) | R@1(%) | R@5(%) | NDCG@5(%) | F1(%) | Response Time(ms) |
|---|---|---|---|---|---|---|---|
| TF-IDF+Cosine | 52.3 | 67.8 | 48.6 | 66.4 | 62.1 | 50.4 | 15 |
| Word2Vec+SVM | 58.7 | 72.1 | 54.2 | 70.8 | 68.3 | 56.3 | 45 |
| BERT-base | 76.8 | 82.4 | 73.1 | 80.9 | 79.2 | 74.9 | 180 |
| Our Method | **83.2** | **89.7** | **81.9** | **88.3** | **87.1** | **82.5** | 240 |
| Improvement | +6.4% | +7.3% | +8.8% | +7.4% | +7.9% | +7.6% | - |

TABLE II
ABLATION STUDY RESULTS OF SYSTEM TECHNICAL COMPONENTS

| Model Configuration | P@1(%) | P@5(%) | R@5(%) | F1(%) | Relative Improvement(%) | Marginal Contribution(%) |
|---|---|---|---|---|---|---|
| BERT Baseline | 76.8 | 82.4 | 80.9 | 74.9 | - | - |
| + Skill Matching | 78.5 | 84.1 | 82.6 | 76.8 | +1.9 | +1.9 |
| + Experience Matching | 80.2 | 86.3 | 84.7 | 79.1 | +4.2 | +2.3 |
| + Soft Skills Evaluation | 81.7 | 87.8 | 86.2 | 80.9 | +6.0 | +1.8 |
| + Weight Optimization (Complete) | **83.2** | **89.7** | **88.3** | **82.5** | **+7.6** | **+1.6** |

TABLE III
MATCHING PERFORMANCE AND FEATURE WEIGHT ANALYSIS BY POSITION TYPE

| Position Type | Sample Size | P@1(%) | Standardization Level | $\alpha$ (Skills) | $\beta$ (Experience) | $\gamma$ (Soft Skills) | Dominant Factor |
|---|---|---|---|---|---|---|---|
| Front Desk Reception | 37 | 89.2 | High | 0.25 | 0.35 | 0.40 | Soft Skills |
| Housekeeping | 53 | 87.6 | High | 0.45 | 0.35 | 0.20 | Skills |
| F&B Service | 39 | 84.3 | Medium | 0.30 | 0.30 | 0.40 | Soft Skills |
| Sales Manager | 23 | 76.8 | Low | 0.30 | 0.40 | 0.30 | Experience |
| F&B Supervisor | 17 | 78.1 | Low | 0.25 | 0.45 | 0.30 | Experience |
| General Manager | 16 | 82.4 | Medium | 0.35 | 0.40 | 0.25 | Experience |

ational capabilities; management decision-oriented positions (sales manager, F&B supervisor, general manager) generally emphasize experience relevance with weights between 0.40-0.45, indicating the key role of management experience and industry background in high-level positions.

## V. CONCLUSIONS AND FUTURE WORK

### A. Main Contributions

This study successfully constructed a large language model-based resume-job intelligent matching system for the hotel industry under limited data conditions, utilizing 1,847 recruitment records spanning 10 years and 29 standardized job descriptions to validate the effectiveness of small sample learning frameworks. Despite limited data scale, the system achieved significant performance improvements through optimized experimental design and technical methods, providing feasible intelligent recruitment solutions for small and medium-scale hotel enterprises. The research validates large language model effectiveness in vertical industry small sample scenarios while offering crucial technical support for digital transformation of hotel human resource management, with the small sample learning strategies and domain adaptation methods providing valuable reference for intelligent recruitment system deployment across other service industries under data-constrained conditions.

(1) **Technical contributions under small sample environments:** Under limited sample conditions of 1,847 samples, we successfully achieved effective application of multi-dimensional matching algorithm frameworks through LoRA fine-tuning technology for efficient domain adaptation of BERT model and designed GBDT weight optimization mechanisms suitable for small sample environments. The technical solution fully considered data scarcity challenges, adopting conservative model parameter configurations, L2 regularization for overfitting prevention, and 3-fold cross-validation strategies to ensure algorithm stability and reliability under limited data. This technical framework optimized for small sample learning provides feasible pathways for small and medium-scale enterprises to apply AI technology under resource-constrained conditions, with important practical guidance significance.

(2) **Hotel industry position characteristic discoveries:** Through in-depth analysis of six major hotel position categories, we successfully revealed strong positive correlation between position standardization degree and matching effects (r = 0.89, p ¡ 0.01) even in small sample environments. We discovered differentiated weight allocation patterns across different position types in skills, experience, and soft skills dimensions: standardized positions (front desk, housekeeping) achieved significantly higher matching accuracy than personalized positions (sales, management), experience relevance plays a dominant role in management positions, and soft skills evaluation is most important in customer service positions. These findings provide data evidence for hotels to formulate

differentiated recruitment strategies while also validating the feasibility of precise analysis under limited sample conditions.

(3) **Empirical performance and generalization capability verification:** The system achieved an overall F1 score of 82.5%, improving 32.1 percentage points over traditional TF-IDF methods and 7.6 percentage points over BERT baseline, with all improvements statistically significant (p ¡ 0.001). Through 5-fold cross-validation, model performance standard deviation was controlled within ±2.1%, demonstrating good stability. In robustness testing with 30% data missing, system performance decreased by only 5.8%, proving anti-noise capability. These results indicate that even under relatively small data scales, carefully designed technical solutions can still achieve satisfactory results, providing confidence assurance for small-scale hotel enterprises to deploy intelligent recruitment systems.

### *B. Research Limitations and Future Work*

This study presents several limitations and future research directions. The research limitations include data constraints from a single hotel group with limited sample size, potentially affecting model generalization; reliance solely on textual information without incorporating multimodal data such as video interviews and psychological assessments; temporal evolution factors not adequately considered across the 10-year data collection period; and lack of long-term deployment tracking studies. Future work should address these limitations through five key directions: expanding data collection by collaborating with multiple hotel enterprises to build larger, more representative datasets; exploring multimodal information fusion technologies to integrate diverse data sources for comprehensive candidate evaluation; conducting longitudinal studies to analyze system performance and user satisfaction in real applications; extending the framework to other service industries to validate cross-industry applicability; and implementing federated learning approaches to enable collaborative optimization while protecting enterprise data privacy, thereby improving model generalization and small-sample learning efficiency.

## REFERENCES

[1] P. Skondras, P. Zervas, and G. Tzimas, "Generating synthetic resume data with large language models for enhanced job description classification," *Future Internet*, vol. 15, no. 11, p. 363, 2023.

[2] H. Kavas, M. Serra-Vidal, and L. Wanner, "Using large language models and recruiter expertise for optimized multilingual job offer–applicant CV matching," in *Proc. 33rd Int. Joint Conf. Artificial Intelligence* , Jeju, Republic of Korea, Aug. 2024, pp. 3-9.

[3] A. R. Vishaline, R. K. Kumar, V. V. N. S. Sai Pramod, K. V. K. Vignesh, and P. Sudheesh, "An ML-based resume screening and ranking system," in *Proc. 2021 Int. Conf. Signal Processing, Computation, Electronics, Power and Telecommunication* , Karaikal, India, Jul. 2024, pp. 1-6.

[4] S. Bharadwaj, R. Varun, P. S. Aditya, M. Nikhil, and G. C. Babu, "Resume screening using NLP and LSTM," in *Proc. 2022 Int. Conf. Inventive Computation Technologies*, Lalitpur, Nepal, Jul. 2022, pp. 238-241.

[5] D. Lavi, V. Medentsiy, and D. Graus, "ConsultantBERT: Fine-tuned siamese sentence-BERT for matching jobs and job seekers," *arXiv preprint arXiv:2109.06501*, 2021.

[6] B. Kinge, S. Mandhare, P. Chavan, and S. M. Chaware, "Resume screening using machine learning and NLP: A proposed system," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 8, no. 2, pp. 253-258, 2022.

[7] T. M. Harsha, G. S. Moukthika, D. S. Sai, M. N. R. Pravallika, S. Anamalamudi, and M. Enduri, "Automated resume screener using natural language processing (NLP)," in *Proc. 2022 6th Int. Conf. Trends in Electronics and Informatics*, Coimbatore, India, Apr. 2022, pp. 1772-1777.

[8] A. Peña, I. Serna, A. Morales, J. Fierrez, A. Ortega, A. Herrarte, and J. Ortega-Garcia, "Human-centric multimodal machine learning: Recent advances and testbed on AI-based recruitment," *SN Computer Science*, vol. 4, no. 5, p. 434, 2023.

[9] I. Ali, N. Mughal, Z. H. Khand, J. Ahmed, and G. Mujtaba, "Resume classification system using natural language processing and machine learning techniques," *Mehran University Research Journal of Engineering and Technology*, vol. 41, no. 1, pp. 65-79, 2022.

[10] A. Jalili, H. Tabrizchi, J. Razmara, and A. Mosavi, "BiLSTM for resume classification," in *Proc. 2024 IEEE 22nd World Symposium on Applied Machine Intelligence and Informatics*, Poprad, Slovakia, Jan. 2024, pp. 519-524.

[11] X. Yu, J. Zhang, and Z. Yu, "Confit: Improving resume-job matching using data augmentation and contrastive learning," in *Proc. 18th ACM Conf. Recommender Systems*, Oct. 2024, pp. 601-611.

[12] Z. Zheng, Z. Qiu, X. Hu, L. Wu, H. Zhu, and H. Xiong, "Generative job recommendations with large language model," *arXiv preprint arXiv:2307.02157*, 2023.

[13] E. Salakar, J. Rai, A. Salian, Y. Shah, and J. Wadmare, "Resume screening using large language models," in *Proc. 2023 6th Int. Conf. Advances in Science and Technology*, Karaikal, India, Dec. 2023, pp. 494-499.

[14] S. Haryan, R. Malik, P. Redij, and S. Kulkarni, "FairHire: A fair and automated candidate screening system," in *Int. Conf. Machine Intelligence, Tools, and Applications*, Springer, 2024, pp. 372-382.

[15] P. Ghosh and V. Sadaphal, "JobRecoGPT–explainable job recommendations using LLMs," *arXiv preprint arXiv:2309.11805*, 2023.

[16] M. E. Erdem, "Automatic resume screening with content matching," in *Proc. 2023 8th Int. Conf. Computer Science and Engineering*, Antalya, Turkey, Oct. 2023, pp. 554-558.

[17] Y. Du, D. Luo, R. Yan, X. Wang, H. Liu, H. Zhu, Y. Song, and J. Zhang, "Enhancing job recommendation through LLM-based generative adversarial networks," in *Proc. AAAI Conf. Artificial Intelligence*, vol. 38, 2024, pp. 8363-8371.

[18] A. H. AL-Qassem, K. Agha, M. Vij, H. Elrehail, and R. Agarwal, "Leading talent management: Empirical investigation on applicant tracking system (ATS) on e-recruitment performance," in *Proc. 2023 Int. Conf. Business Analytics for Technology and Security*, Dubai, UAE, Mar. 2023, pp. 1-5.

[19] A. Magron, A. Dai, M. Zhang, S. Montariol, and A. Bosselut, "JobSkape: A framework for generating synthetic job postings to enhance skill matching," *arXiv preprint arXiv:2402.03242*, 2024.

[20] L. Wang, N. Yang, X. Huang, L. Yang, R. Majumder, and F. Wei, "Multilingual E5 text embeddings: A technical report," *arXiv preprint arXiv:2402.05672*, 2024.

[21] P. Q. Wang, "Personalizing guest experience with generative AI in the hotel industry: There's more to it than meets a Kiwi's eye," *Current Issues in Tourism*, vol. 28, no. 4, pp. 527-544, 2025.

[22] F. P. W. Lo, J. Qiu, Z. Wang, H. Yu, Y. Chen, G. Zhang, and B. Lo, "AI hiring with LLMs: A context-aware and explainable multi-agent framework for resume screening," in *Proc. Computer Vision and Pattern Recognition Conf.* , 2025, pp. 4184-4193.

[23] M. Łepicki, T. Latkowski, I. Antoniuk, M. Bukowski, B. Świderski, G. Baranik, B. Nowak, R. Zakowicz, Ł. Dobrakowski, B. Act, and J. Kurek, "Comparative evaluation of sequential neural network (GRU, LSTM, transformer) within Siamese networks for enhanced job–candidate matching in applied recruitment systems," *Applied Sciences*, vol. 15, no. 11, p. 5988, 2025.

[24] E. Albaroudi, T. Mansouri, and A. Alameer, "A comprehensive review of AI techniques for addressing algorithmic bias in job hiring," *AI*, vol. 5, no. 1, pp. 383-404, 2024.

[25] Y. Mashayekhi, N. Li, B. Kang, J. Lijffijt, and T. De Bie, "A challenge-based survey of e-recruitment recommendation systems," *ACM Computing Surveys*, vol. 56, no. 10, pp. 1-33, 2024.