2025 Volume 3, Issue 5
Educational Innovation Research
ISSN: 3029-1844(Print)
ISSN: 3029-1852(Online)

Research on Intelligent Competency Modeling and Job-Person Matching Mechanism Based on the DeepSeek Model

Biao Wang[1,2]
[1] Zibo Housing Provident Fund Management Center, Zibo 255100, Shandong, China
[2] "Silk Road" International University of Tourism and Cultural Heritage, Samarkand city 140104, Republic of Uzbekistan

Abstract

With the rapid development of artificial intelligence, especially open-source large language models, enterprise human resource management is undergoing profound transformation. Traditional competency models for job positions largely rely on expert experience for construction, which leads to outdated updates, poor generalizability, and an inability to meet the rapidly changing strategic needs of modern organizations [1]. This paper proposes a low-cost, scalable competency modeling and job-person matching framework based on DeepSeek, a representative open-source language model. By applying natural language processing and semantic embedding techniques, the system extracts competency elements from job descriptions and resumes to construct ability vectors and compute job-person matching scores. The study also explores the application of this model in scenarios such as recruitment screening, job adjustment, and talent development, and identifies challenges such as data quality, model interpretability, and digital literacy among HR professionals, while proposing corresponding countermeasures. Experiments and preliminary applications demonstrate that the intelligent competency system based on large language models is highly feasible and commercially valuable [2].

Keywords

artificial intelligence
competency model
job-person matching
deepseek
natural language processing
digital human resources

Online publication: June 26, 2025

1. Introduction

In the rapidly evolving digital economy, enterprises are increasingly demanding precise matches between talent and job positions. Traditional human resource management methods that rely heavily on subjective experience are being fundamentally reshaped. The competency model, as a critical intermediary connecting job requirements with employee capabilities, has been widely applied in recruitment, performance evaluation, promotion assessments, and training systems.

However, traditional competency models are often constructed using methods such as the Delphi technique, behavioral event interviews (BEI), or expert workshops. These methods are time-consuming, costly, and lack general applicability, making them unsuitable for rapidly changing business environments [3]. Moreover, statically defined competency dimensions struggle to capture the dynamic evolution of job requirements and fail to effectively identify deep-level talent capabilities.

In recent years, breakthroughs in artificial intelligence, especially in the field of natural language processing (NLP), have brought about a fundamental shift in competency modeling paradigms. Open-source language models such as DeepSeek possess powerful semantic understanding and embedding capabilities, enabling the transformation of unstructured texts—such as job descriptions, resumes, and performance records—into unified semantic vectors representing competencies. This allows for matching and analysis based on a shared "competency space" [4].

Unlike traditional systems based on keyword retrieval or rule-based matching, large language models can recognize semantically similar expressions and identify transferable skills across industries and job types, significantly improving the precision and fairness of job-person matching [5]. At the same time, DeepSeek, as a free, open-source, and fine-tunable model, offers small and medium-sized enterprises a low-barrier, high-performance AI solution that significantly reduces the deployment cost of intelligent matching systems.

Therefore, this paper aims to construct a competency modeling and job-person matching framework centered on DeepSeek, integrating natural language processing, competency vector modeling, and organizational practice needs. It explores the implementation of modules such as job modeling, talent recommendation, and competency gap analysis, and conducts in-depth analysis of challenges encountered in real-world enterprise deployment, offering targeted solutions [6].

2. AI-Driven Competency Modeling and Job-Person Matching Mechanism

The development of artificial intelligence, particularly natural language processing (NLP) technologies, is fundamentally reshaping the underlying logic of traditional competency modeling. In the past, competency models were manually constructed by HR experts using interviews, surveys, and workshops. These methods were not only inefficient and limited in scope, but also difficult to update in real time. Today, the powerful semantic processing capabilities of large language models enable the automatic extraction of competency dimensions from unstructured text.

2.1. Semantic Modeling Mechanism for Job Competency

In traditional HR practices, job descriptions (JDs) are an important source for constructing competency models. However, these documents often suffer from inconsistencies in language style and loose structural organization. Large language models such as DeepSeek can utilize multi-layer semantic representations built through self-supervised training to vectorize these texts and embed them into high-dimensional semantic spaces, enabling automatic extraction and classification of core responsibilities, skill requirements, and behavioral traits [7].

In practical application, the system first performs preprocessing on JD texts, including tokenization, named entity recognition, and dependency parsing. It then employs a deep semantic network to identify competency elements directly related to job tasks, such as "problem-solving skills," "cross-functional communication," or "Python programming." These competency labels can further be aligned with existing enterprise competency frameworks, such as O*NET or proprietary corporate models, to form a structured competency taxonomy.

Ultimately, each job is encoded into a vector representation containing multiple competency dimensions. This representation serves as the foundational information unit for subsequent job-person matching processes. This approach not only significantly reduces manual intervention but also enhances the adaptability and scalability of the competency modeling system.

2.2. Logic of Generating Candidate Competency Profiles

In a job-person matching system, candidate information must also be converted into competency vectors to enable comparison with job profiles. Candidate-related texts include resumes, cover letters, project experience, and public portfolio links. The system applies semantic embedding techniques to extract embedded knowledge, skills, experiences, and behavioral traits.

For instance, a resume stating "Led an AI algorithm transformation for an educational platform, improving learning path recommendation accuracy" can be semantically interpreted by the system to infer competencies such as "algorithm development," "data modeling experience," and "team collaboration." These elements are then quantified and mapped into the semantic space. Importantly, the candidate need not use standardized terminology, as the model is capable of actively recognizing implicit expressions of competencies, thereby significantly improving inclusiveness and accuracy in competency extraction.

To enhance matching precision, the system must also introduce a weighting mechanism among competency dimensions. For example, if a position emphasizes communication and learning capabilities, the system should assign higher weights to these dimensions when calculating the match score. This logic can be iteratively optimized based on actual recruitment feedback.

2.3. Design of Job-Person Matching Scoring Mechanism

Once both the job and candidate competency vectors have been constructed, the system can calculate their "competency match score" using mathematical methods such as cosine similarity or Euclidean distance. In addition, it can incorporate minimum thresholds for key competency dimensions, allowing the system to filter out low-fit candidates in the initial screening phase.

For example, in a recruitment scenario where the job requires strong communication skills, project management abilities, and Java proficiency, a candidate who scores highly in communication and Java but slightly lower in project management—yet still above the threshold—can be shortlisted for further evaluation by HR.

To improve acceptability among HR professionals, the system should offer match explanation functions, such as radar charts that visualize competency comparisons, or generate concise rationales that clarify why a candidate was recommended. This helps HR professionals better understand the AI decision-making process and supplement it with their own judgment.

2.4. System Integration and Application Scenarios

Based on the modeling logic described above, enterprises can build a complete closed-loop system connecting "Job–Competency–Talent." This system includes the following functional modules:

Job Competency Library Module: Automatically parses all JD documents within the enterprise and generates structured job competency profiles;

Resume Competency Extraction Module: Semantically analyzes candidate information to produce individual talent profiles;

Matching Score & Recommendation Module: Computes job-candidate match scores and generates explanatory reports;

Feedback Learning Mechanism Module: Continuously updates model weights based on recruitment results and HR feedback, improving recommendation accuracy over time [8].

In real-world practice, this system can be used not only for external hiring but also for internal job rotation, talent inventory analysis, and succession planning. It provides organizations with a dynamic capability analysis tool that supports strategic workforce decisions.

3. Data-Driven Human Resource Management and Organizational Evolution Pathways

The application of AI-powered competency modeling not only improves the efficiency of job-person matching but also lays the groundwork for data-driven human resource systems within enterprises. Traditional HR management relies heavily on subjective judgment and fragmented information, resulting in delayed and inconsistent decision-making—an approach ill-suited for today's agile organizational demands. Once competency data is structured and embedded semantically, organizations can reconceptualize their structure and talent relationships around "capability units," thereby initiating a transformation toward intelligent HR systems.

3.1. Organizational Capability Mapping and Talent Inventory Mechanism

By encoding all positions and employees into a unified competency vector space, companies can build a comprehensive organizational capability map. This map enables the identification of competency redundancies, gaps, or critical deficiencies, which in turn supports more informed decisions in workforce optimization and strategic alignment. For instance, a technology company may discover, via such a map, that project management and cross-functional communication are significantly underrepresented in key departments, prompting a realignment of internal training priorities and external recruitment strategies.

In addition, the system can identify high-potential talent clusters by analyzing patterns in competency growth and capability combinations. HR managers can then proactively earmark these individuals for accelerated development or strategic project assignments.

3.2. Flexible Job-Person Matching and Enhanced Organizational Agility

A data-driven matching model allows organizations to dynamically respond to shifting business requirements, such as job reassignments, structural adjustments, or the formation of temporary project teams. For example, when a company launches a new digital marketing unit, the system can rapidly scan the internal talent pool for employees who simultaneously possess "data analytics" and "market insight" capabilities, and recommend them for an initial pilot team. This competency-based resource deployment mechanism significantly enhances the organization's responsiveness.

Compared to the traditional model of position assignment based on hierarchy or tenure, AI-driven systems follow a more logical sequence of "business problem → capability requirement → talent recommendation," aligning well with project-based and task-driven organizational models [9].

3.3. The Strategic Role of Competency Data in Enterprise Decision-Making

During organizational restructuring or business transformation, many enterprises face a critical mismatch between strategic goals and actual competency reserves. By building a robust competency data infrastructure, leadership teams can leverage the system to forecast capability gaps, estimate transformation costs, and plan training or recruitment needs accordingly.

For example, in a planned expansion into international markets, the system can analyze the distribution and proportion of employees with skills in cross-cultural communication, global business practices, and foreign languages. This enables management to assess redeployment potential and formulate more precise talent acquisition or upskilling strategies [10].

4. Practical Challenges and Mitigation Strategies for AI-Driven Competency Modeling

Despite the substantial potential of AI in job-person matching and competency modeling, real-world implementation presents several complex challenges. When applying open-source large language models such as DeepSeek in human resource management, enterprises must go beyond technical compatibility and address a broader set of issues involving data ethics, organizational culture, and operational mechanisms. This section outlines four key categories of implementation barriers and provides corresponding solutions.

4.1. Data Quality and Diversity Challenges

The performance and iterative refinement of competency models are highly dependent on the quality of input data. In real-world enterprise environments, job descriptions are often characterized by inconsistent terminology, redundant information, and outdated content. Meanwhile, resumes and internal employee capability records are frequently heterogeneous and poorly structured, making it difficult for AI models to learn from reliable inputs.

Furthermore, significant variations exist in how different industries or companies define the same competency. For example, "communication skills" in sales may emphasize client orientation, whereas in technical roles it may relate more to cross-functional collaboration. This diversity challenges the model's generalizability and necessitates industry- or organization-specific fine-tuning.

Proposed Strategies:

Establish standardized annotation guidelines for job and competency data to promote consistency across JD and employee records.

Implement rule-based data cleaning mechanisms combined with machine learning models for noise correction and semantic classification [11].

Employ active learning strategies that prioritize high-confidence samples during training, improving model robustness and learning efficiency[12].

4.2. Limited Model Interpretability and HR Trust Issues

Although models like DeepSeek can deliver high semantic similarity scores in job-person matching, their internal decision-making processes are often opaque. HR professionals may encounter the "black box" problem, struggling to understand why a candidate was recommended, whether the system exhibits bias, or whether automated decisions are trustworthy.

In practice, there is growing resistance to AI-based matching systems, particularly when recommendations influence sensitive personnel decisions such as promotions or terminations. HR practitioners tend to favor human judgment over opaque algorithmic outputs in such scenarios.

Proposed Strategies:

Introduce model interpretability modules using methods such as Shapley values, attention visualization, or vector mapping to illustrate how specific competency dimensions drive recommendations [13].

Adopt a hybrid decision-making model that combines AI recommendations with HR expert judgment, fostering greater transparency and human oversight.

Generate explanatory reports for each match, including radar charts for competency comparison, skill alignment breakdowns, and narrative justifications for recommendations.

4.3. Organizational Culture and HR Capability Fit

Implementing an AI system is not merely a technological shift—it entails a profound organizational transformation. If the HR team lacks digital literacy or prior experience with data tools, there is a risk that the system will be deployed but not adopted.

This issue is particularly pronounced in traditional industries or state-owned enterprises, where HR professionals often exhibit skepticism toward AI. Concerns about job displacement, system compatibility, and general distrust of technology can severely undermine model effectiveness.

Proposed Strategies:

Involve HR teams in system co-design through collaborative frameworks where both HR and data science teams jointly define matching rules and competency taxonomies.

Launch upskilling programs to enhance digital literacy and support the transition from transactional HR roles to data-driven HR practices.

Embed AI modules directly into existing HR platforms (e.g., ATS, OA, or HRIS systems) to lower the barrier to usage and streamline user experience[14].

4.4. Ethical Risks and Data Privacy Protection

Job-person matching systems inevitably process sensitive personal information such as education background, gender, age, and performance records. Without robust data governance and ethical safeguards, these systems can lead to:

Lack of algorithmic neutrality, causing implicit discrimination (e.g., favoring male candidates or penalizing career switchers);

Internal leakage of employee competency profiles, resulting in coercive performance monitoring;

Unconsented data circulation across systems, posing privacy risks for job candidates.

Proposed Strategies:

Integrate fairness-aware algorithms to detect and mitigate bias in model outputs, ensuring that recommendations are not distorted by non-competency factors such as age or gender[14].

Establish robust data authorization protocols to guarantee that every instance of data use is legally grounded and traceable.

Develop an "AI Ethics Usage Framework" that embeds principles of transparency, auditability, and privacy protection into the system development lifecycle[15].

5. Future Outlook: Building an AI-Powered Competency Ecosystem

With the convergence of large language models, knowledge graphs, and multimodal interaction technologies, AI-driven competency systems are evolving from standalone tools into strategic-level ecosystems.

Enterprises will no longer use AI solely for recruitment and matching, but rather as the foundation for an intelligent network centered around "capability" that spans the entire talent lifecycle.

5.1. From Static Models to Dynamic Competency Evolution Systems

Future competency models will not remain static structures defined in advance, but will evolve continuously through real-time data and automated updates. Behavioral data from employees' project participation, learning trajectories, and performance feedback will feed into the system, allowing for dynamic optimization of competency profiles. Consequently, job-person fit will evolve from a one-time matching exercise into a predictive model of long-term potential.

5.2. Deep Integration with Talent Development Systems

AI competency systems will be integrated with online learning platforms, performance management systems, and career path planning tools to form a closed loop of "gap identification → learning recommendation → competency update." For example, if a candidate lacks communication skills for a particular position, the system can automatically suggest micro-courses or mentorship resources to help narrow the competency gap.

5.3. Evolution into a Strategic Decision Support Platform

Leveraging enterprise-wide competency maps, AI can assist in designing more effective organizational structures and talent distributions. For instance, if the system identifies a lack of data-driven operational skills within a regional sales team, it can recommend adjusting organizational responsibilities or introducing new competency models. In this way, HR transitions from a support function to a strategic driver of organizational evolution.

6. Conclusion

This study explored the application of the open-source large language model DeepSeek in building intelligent competency modeling and job-person matching systems. It proposed a low-cost, highly adaptable AI-driven solution for identifying and recommending talent capabilities. Compared to traditional methods, this system offers superior semantic understanding, high matching accuracy, and strong scalability.

In terms of modeling, the system automatically extracts competency elements from unstructured job and resume texts, enabling semantic alignment between job and talent profiles. It is applicable not only to external recruitment but also to job rotation, organizational capability mapping, and talent development planning. The system further facilitates the transformation of HR from an administrative role into a data-driven, strategic partner.

Despite its advantages, practical implementation of AI competency systems still faces challenges such as fragmented data, limited model interpretability, and organizational resistance. Future systems must evolve toward multimodal capability recognition, self-supervised learning, and deep integration with talent development platforms to form a full-stack human resource management ecosystem centered on competencies.

This research illustrates that AI is not merely a tool for job matching, but a technological cornerstone for organizational design and strategic transformation. As open-source model performance improves and technical barriers decline, the widespread adoption of competency systems will become a critical pathway for enhancing enterprise talent competitiveness.

Disclosure statement

The author declares no conflict of interest.

References

[1] Gong, M., Fu, Y., Yao, J., et al., 2024, Bibliometric analysis of research on employee competency models in China. *Modern Management*, 14(8), 2036–2048.

[2] Maurer R, 2024, Talent Acquisition Trends Led by GenAI, Skills-Based Hiring. SHRM.

[3] Wang J, 2013, Application of competency models in university talent dispatch projects [Master's thesis, Capital University of Economics and Business].

[4] Qin, C., Zhang, L., Cheng, Y., Shen, D., Zhu, C., Zhu, H., et al., 2023, A comprehensive survey of artificial intelligence techniques for talent analytics. *arXiv preprint* arXiv:2302.12347.

[5] Bohlouli M., Mittas N., Kakarontzas G., et al., 2020, Competence assessment as an expert system for human resource management: A mathematical approach. arXiv preprint arXiv:2001.00739.

[6] Robert L. P., Pierce C., Morris L., Kim S., & Alahmad R, 2020, Designing fair AI for managing employees in organizations: A review, critique, and design agenda. arXiv preprint arXiv:2001.00965.

[7] VanderMeulen N., & Leidner D., 2024, Resolving Workforce Skills Gaps with AI-Powered Insights. MIT CISR Research Briefing, 2024-0401.

[8] AIHR, 2024, HR Competency Model. Amsterdam: AIHR Research Institute.

[9] CPI Knowledge Classroom, 2024, Decoding competency models: A panoramic guide [Zhihu column]. Retrieved June 28, 2025, from https://zhuanlan.zhihu.com/p/671046312

[10] Robert L. P., Pierce C., Morris L., Kim S., & Alahmad R., 2020, Designing fair AI for managing employees in organizations: A review, critique, and design agenda. arXiv preprint arXiv:2001.00965

[11] Construction of competency models for assistant general practitioners in China based on the Delphi and AHP methods. General Practice, 2023, 21(2).

[12] Smith A., & Jones R., 2023, Active learning in NLP-based HR systems: overcoming practical implementation hurdles. Computational Linguistics, 49(4), 209–231.

[13] Johnson H., Patel V., & Kim S., 2021, Explainable AI in HR: deploying XAI tools for transparent decision support. AI Magazine, 42(2), 67–79.

[14] Chen X., Li Y., & Wang J., 2024, Fairness, transparency, and accountability in AI-driven talent acquisition: A review. Journal of Business Ethics, 180(1), 45–65.

[15] Allen T., Berg M., & Cummings J., 2022, AI ethics frameworks for enterprise-grade talent management systems. Journal of Business Ethics, 174(3), 421–437.