



A Review of Skill-Based Matching Systems for Workforce Management

1. Prof. Swati Sagar
2. Soham Vede
3. Soham Yadav
4. Sarthak Katyare
5. Rushikesh Shinde

MCA Department, ASM's Institute of Business Management and Research, Chinchwad, Pune, Maharashtra, India

Corresponding Author Email: sohamvede2004@email.com

Abstract—

How to Cite this Article:

Vede, S., Yadav, S., Katyare, S. & Shinde, R. (2026). A Review of Skill-Based Matching Systems for Workforce Management. International Journal of Creative and Open Research in Engineering and Management, 2(10), 1-9. <https://doi.org/10.55041/ijcope.v2i10.127>

License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i10.127>

Skill-based matching has become an important part of digital workforce management because organizations and employment platforms need to connect job requirements with workers who possess relevant competencies. Traditional approaches often depend on manual searching, job titles, resumes, or simple keyword filters, which may overlook differences in skill level, experience, availability, location, and other practical factors. This review examines existing research on skill-based matching, job recommendation, worker-job matching, and related workforce management systems. The reviewed approaches include keyword and content-based matching, similarity-based methods, knowledge-based and ontology-driven approaches, multi-criteria matching, context-aware recommendation, and hybrid systems. Recent systematic reviews identify continuing challenges involving skill representation, standardization, explainability, fairness, interoperability, and evaluation. The review also compares how different approaches represent workers and jobs and how they support ranking and recommendation. The findings indicate that skill matching becomes more useful when combined with contextual factors such as experience, availability, location, and job preferences. The paper concludes with research gaps and future directions for transparent and practical workforce-management systems.

Keywords— Skill Matching; Workforce Management; Job Recommendation; Worker-Job Matching; Multi-Criteria Matching; Skill-Based Recommendation



I. INTRODUCTION

Workforce management is concerned with planning, assigning, and coordinating people so that available skills and resources are aligned with work requirements. One of the most important activities in this process is identifying a suitable worker for a particular job. In traditional environments, this may involve checking resumes, contacting workers, comparing qualifications, and manually filtering candidates. When many workers and jobs are involved, such a process becomes time-consuming and may make it difficult to compare several criteria consistently.

The growth of online employment and service platforms has created structured information about job seekers, workers, job descriptions, qualifications, experience, preferences, and previous work. This has encouraged the use of recommendation and matching systems to reduce information overload. Job recommender systems attempt to connect people with relevant employment opportunities, while worker recommendation systems help employers or customers identify appropriate candidates. A 2025 systematic literature review describes content-based, collaborative, hybrid, knowledge-based, and context-aware approaches as important areas of job recommender research [1].

Skill information is particularly important because a job usually requires a combination of abilities rather than a single job title. A worker may have several skills with different levels of experience, while a job may contain mandatory and optional requirements. Simple keyword matching can identify exact words but may fail when similar competencies are described differently. Malinowski et al. demonstrated the importance of bilateral recommendation, where both the candidate and the recruiter side of the employment relationship can be considered [2].

Recent work has expanded the representation of jobs and workers using structured competencies, semantic relationships, machine learning features, and contextual information. A 2026 literature review found that job, skill, and competency representations remain heterogeneous and highlighted standardization, explainability, fairness, and interoperability as important research challenges [3].

This review therefore focuses specifically on skill-based matching systems from a workforce-management perspective. It examines the main matching techniques, the attributes used, evaluation methods, limitations, and research opportunities.

II. LITERATURE REVIEW

A. Recommender Systems and Employment Matching

Recommender systems were initially developed to help users discover relevant items from large collections. The general recommender-system literature includes content-based, collaborative, and hybrid approaches [4], [5]. In employment applications, the recommended item is not a product but a job, worker, or candidate. This changes the problem because the suitability of a recommendation can depend on requirements from both sides.

Employment recommendation is therefore often treated as a matching problem. The system needs to represent the worker and the job in a form that allows comparison. Malinowski et al. proposed a bilateral recommendation approach in which both candidate and recruiter preferences are considered [2]. This idea is relevant to workforce platforms where a worker's skills must match the job while practical factors such as availability and expected compensation also matter.

B. Skill Representation

A central issue in skill-based matching is how skills are represented. A simple representation can store skills as a list, while a richer representation may include skill level, years of experience, certification, related competencies, and occupational context. The 2026 review by Spoladore et al. reports that existing systems use heterogeneous representations of skills and competencies, making interoperability and consistent matching difficult [3].

Standardized occupational and skill resources can reduce ambiguity, but they do not automatically solve the problem of proficiency or practical experience. Two workers may both have the same named skill but differ considerably in skill level. A workforce-management system therefore benefits from distinguishing skill presence from skill proficiency and verified experience.

C. Content-Based and Similarity Matching

Content-based matching compares job characteristics with worker characteristics. A job can be represented using required skills, experience, location, work type, and other attributes, while a worker can be represented using skills, experience, qualifications, preferences, and availability. Similarity is then calculated between the two representations [4], [9].



Similarity-based techniques provide a direct way to rank candidates. Cosine similarity is frequently used when text or feature vectors are available, while multi-criteria methods can combine several normalized values. The 2025 systematic review identifies similarity-based techniques and multi-criteria decision methods among the approaches used in job recommender research [1].

D. Knowledge-Based and Semantic Matching

Knowledge-based matching uses domain knowledge, rules, ontologies, or structured competency relationships. Instead of requiring two descriptions to use exactly the same word, a knowledge structure can indicate that related skills belong to the same competency area. This can make recommendations easier to explain because the matching path can be represented as explicit rules or relationships.

The main difficulty is maintaining the knowledge base. Skill taxonomies change over time, occupations evolve, and different platforms may represent the same competency in different ways. The recent literature also reports interoperability and ontology-engineering challenges in knowledge-driven job recommendation systems [3].

E. Multi-Criteria and Context-Aware Matching

A worker's skill match is only one part of practical suitability. Experience, availability, location, wage expectations, credentials, ratings, and job preferences can also influence the decision. Multi-criteria matching combines these attributes instead of treating the skill match as the only variable.

Context-aware approaches extend this idea by considering information that changes with the situation, such as job date, distance, current availability, work duration, or emergency status. Such information is especially important in local service work, where a worker with the correct skill may still be unsuitable if the worker cannot reach the job or is unavailable.

F. Hybrid Recommendation

Hybrid systems combine two or more recommendation approaches. The purpose is to reduce weaknesses associated with relying on a single technique. For example, a system may combine content similarity with collaborative information, or combine a structured knowledge model with data-driven ranking. Hybrid recommender systems have long been studied as a way to combine complementary strengths [5]. Recent employment-recommendation literature continues to identify hybrid approaches as an area of interest, although integrating heterogeneous representations remains challenging [1], [3].

Table I. Summary of Selected Literature and Research Focus

Study	Focus	Approach	Key observation
Adomavicius & Tuzhilin [4]	Recommender systems	Survey	Provides foundations for recommendation approaches.
Burke [5]	Hybrid recommendation	Hybrid	Combining methods can address limitations of individual approaches.
Herlocker et al. [6]	Evaluation	Evaluation	Shows the importance of systematic recommender evaluation.
Malinowski et al. [2]	People-job matching	Bilateral	Both candidate and recruiter preferences can matter.
Jannach et al. [7]	Recommender systems	Book/synthesis	Covers recommendation methods and evaluation concepts.
Ricci et al. [8]	Recommender systems	Handbook	Provides broad coverage of recommendation techniques.
Çelik Ertuğrul & Bitirim [1]	Job recommenders	Systematic review	Identifies techniques, applications, metrics, and open challenges.
Spoladore et al. [3]	Job/skill representation	Systematic review	Highlights heterogeneous skill representation, fairness, and explainability.



III. METHODOLOGY

This paper uses a focused literature-review methodology. The review scope was defined around skill-based matching and its use in workforce management. Literature dealing with job recommendation, worker-job matching, recommender systems, skills and competencies, and related evaluation was considered.

A. Search and Selection

The review uses established academic literature and recent review studies as the main evidence base. The literature was grouped according to matching technique and research focus rather than treating all recommendation systems as identical. Studies were retained when they addressed job recommendation, worker-job matching, skill representation, workforce allocation, recommendation evaluation, or a closely related problem.

Recent systematic reviews were used to understand the overall research landscape, while foundational recommender-system and employment-matching studies were used to explain the development of the field [1], [2], [4], [5].

B. Review Categories

- Skill and keyword matching
- Content-based and similarity-based matching
- Knowledge-based and semantic matching
- Multi-criteria matching
- Context-aware matching
- Hybrid recommendation and bilateral matching
- Evaluation and fairness

C. Conceptual Review Framework

The review considers a matching system as a sequence of representation, comparison, ranking, and evaluation. First, worker and job information is represented. Second, relevant attributes are compared. Third, compatible workers or jobs are ranked. Finally, the ranking is evaluated using accuracy, relevance, user, or operational measures.

Worker Profile → Skill/Experience Representation → Matching Criteria → Suitability Calculation → Ranking → Evaluation

IV. RESULTS AND DISCUSSION

Because this paper is a review paper, no new matching model was trained and no original numerical accuracy result is claimed. Instead, this section reviews the evaluation measures commonly used to judge matching and recommendation systems.

A. Precision and Recall

Precision measures how many recommended results are relevant, while recall measures how many relevant

results are successfully retrieved. Both measures are useful when a system returns a set of workers or jobs.

B. F1-Score

F1-score combines precision and recall into a single value. It is useful when both retrieving relevant results and avoiding irrelevant recommendations are important.

C. Ranking Measures

Matching systems often produce a ranked list. Measures such as Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (NDCG) can evaluate whether relevant results appear near the top of the list. Herlocker et al. emphasized the importance of careful recommender-system evaluation and the choice of measures according to the intended use [6].

D. Practical Workforce Measures

For workforce management, offline ranking accuracy is not the only useful measure. Other measures can include time taken to find a suitable worker, number of searches required, response time, user satisfaction, successful job completion, and the clarity of recommendation explanations. These measures connect the technical performance of the matching engine with actual workforce outcomes.

E. Results Analysis

F. Findings from the Review

The literature indicates a gradual shift from simple keyword matching toward richer worker and job representations. Early recommender-system research established content-based, collaborative, and hybrid approaches [4], [5]. Employment-focused research extended these ideas to candidate-job matching, including bilateral recommendation [2]. More recent work has placed greater attention on skill and competency representation, contextual information, fairness, and explainability [1], [3].

A common finding is that no single criterion fully describes worker suitability. Skills are essential, but experience can indicate depth of knowledge, availability determines whether a worker can perform the job when needed, and location can affect the practicality of local work. Credentials and ratings can provide additional evidence of qualification and previous performance.



G. Comparison of Matching Approaches

Table II. Comparison of Matching Approaches

Approach	Main input	Strength	Main limitation
Keyword	Words/terms	Simple and fast	Weak semantic understanding
Content-based	Profiles and job content	Personalized	Depends on data quality
Similarity	Feature vectors	Supports ranking	Feature design matters
Knowledge-based	Skills/competencies/rules	Interpretable	Knowledge engineering effort
Multi-criteria	Multiple attributes	Comprehensive	Requires weighting
Context-aware	Profile context plus	Situation-sensitive	Needs current context
Hybrid	Multiple methods	Combines strengths	Higher complexity

H. Research Gaps

- Skill standardization: different systems may use different names or structures for similar skills.
- Skill proficiency: skill presence does not always show the worker's actual level or depth of experience.
- Real-time availability: worker availability is often difficult to maintain accurately.
- Location and context: local and emergency jobs require practical contextual information in addition to skill similarity.
- Explainability: users need understandable reasons for why a recommendation appears.
- Fairness: automated employment recommendations can reflect biases present in data or system design.
- Interoperability: skill taxonomies and competency models may not work consistently across platforms.
- Broader evaluation: recommendation quality should be connected to user and operational outcomes, not only offline metrics.

I. Discussion

The review suggests that a useful workforce-matching system should treat skills as a foundation rather than the complete decision. A multi-criteria design can combine technical suitability with practical constraints.

At the same time, transparent criteria are valuable because users may want to understand why one worker appears before another. The 2026 review specifically identifies standardization, explainable and fair mechanisms, and hybrid architectures as important directions for job recommender research [3].

Another important observation is the difference between a job portal and a workforce-management system. A portal may primarily recommend jobs or candidates, whereas a workforce-management platform can also consider availability, scheduling, location, workforce requirements, job duration, feedback, and emergency requests. Integrating these functions remains an area where further applied research can be valuable.

V. CONCLUSION

Skill-based matching is an important foundation for workforce management because it provides a structured way to connect job requirements with worker capabilities. The reviewed literature shows that keyword matching, content-based methods, similarity measures, knowledge-based systems, multi-criteria methods, context-aware recommendation, and hybrid approaches have all contributed to this field.

The review also shows that skills alone do not always provide a complete picture of worker suitability. Experience, availability, location, credentials, wage expectations, and previous performance may influence whether a match is practical. At the same time, research continues to face challenges involving skill standardization, heterogeneous representations, explainability, fairness, interoperability, and evaluation [1], [3].

Future systems can therefore move toward transparent multi-criteria workforce matching that combines skill compatibility with relevant contextual information. Such systems should also provide understandable reasons for recommendations and evaluate success using both technical ranking measures and practical workforce outcomes. These directions can support the development of more useful and user-centered workforce-management platforms.

REFERENCES

- [1] D. Çelik Ertuğrul and S. Bitirim, "Job recommender systems: A systematic literature review, applications, open issues, and challenges," *Journal of Big Data*, vol. 12, Art. no. 140, 2025, doi: 10.1186/s40537-025-01173-y.
- [2] J. Malinowski, T. Keim, O. Wendt, and T. Weitzel, "Matching people and jobs: A bilateral recommendation approach," in *Proc. 39th Annu.*



Hawaii Int. Conf. Syst. Sci. (HICSS), Kauai, HI, USA, 2006, pp. 137–146, doi: 10.1109/HICSS.2006.266.

[3] D. Spoladore, S. Criscuolo, and F. Isgrò, “Representing jobs and job seekers in AI-based recommender systems: A literature review,” *Engineering Applications of Artificial Intelligence*, vol. 174, Art. no. 114450, 2026, doi: 10.1016/j.engappai.2026.114450.

[4] G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,” *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, Jun. 2005.

[5] R. Burke, “Hybrid recommender systems: Survey and experiments,” *User Modeling and User-Adapted Interaction*, vol. 12, no. 4, pp. 331–370, 2002.

[6] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, “Evaluating collaborative filtering recommender systems,” *ACM Trans. Inf. Syst.*, vol. 22, no. 1, pp. 5–53, Jan. 2004.

[7] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich, *Recommender Systems: An Introduction*. Cambridge, U.K.: Cambridge Univ. Press, 2010.

[8] F. Ricci, L. Rokach, and B. Shapira, Eds., *Recommender Systems Handbook*, 3rd ed. New York, NY, USA: Springer, 2022.

[9] P. Lops, M. de Gemmis, and G. Semeraro, “Content-based recommender systems: State of the art and trends,” in *Recommender Systems Handbook*, F. Ricci, L. Rokach, and B. Shapira, Eds. Boston, MA, USA: Springer, 2011, pp. 73–105.

[10] G. Adomavicius, B. Mobasher, F. Ricci, and A. Tuzhilin, “Context-aware recommender systems,” *AI Magazine*, vol. 32, no. 3, pp. 67–80, 2011.