

AI-Driven Competency Mapping Framework for Future-Ready Talent Development

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Abstract- The fast development of technologies, automation, and digitalization processes have led to a considerable disruption of how workforce planning is traditionally performed and have created a significant gap between the skills of the existing workforce and the skills that will be necessary in the future for the success of organizations. The process of competency mapping which includes the identification, evaluation, and alignment of skills with strategic goals is extremely important to ensure future readiness via skill development. This paper introduces a new approach to the competency mapping using artificial intelligence, which utilizes NLP algorithms for skill extraction from unstructured sources (resumes, job descriptions, and performance evaluations), GNNs for skill adjacency and competency modeling, and BKT for prediction of the evolution of individual skills. When applied to a database of 50,000 employees in a multinational technology company, our approach yields an accuracy of 89.7% for skill extraction, 82% for skill adjacencies, and 76% for the prediction of future skill gaps. The proposed approach allows us to create personalized learning paths and reduce time-to-competency by 34% in six months.

Key Word: AI-driven Talent Development, Competency Mapping, Skill Extraction, Natural Language Processing (NLP), Graph Neural Networks (GNNs), Bayesian Knowledge Tracing (BKT), Workforce Planning, Upskilling, Learning Pathways, Future-Ready Skills.

I. INTRODUCTION

The modern workplace is witnessing a tectonic shift due to the adoption of technologies like artificial intelligence, automation, cloud computing, and data analytics. According to the WEF's Future of Jobs Report 2025, there could be 85 million jobs lost due to a change in division of labor between man and machine by 2030, but 97 million new jobs created with a better fit for the changed division of labor [1]. While this disruption is primarily technological, it also stems from the rapidly changing set of required skills. For example, the half-life of a skill that a person learns is less than five years on average. And in case of tech skills, it is even shorter.

Organizations must confront this pressing issue: How can we understand which skills our employees possess now and develop skills necessary for tomorrow? Traditional methods of talent management systems are inadequate in this regard. For instance, annual performance reviews, fixed job descriptions, and one-size-fits-all training catalogues are all obsolete and static ways of understanding skills [2]. Organizations need solutions that will help capture the ever-changing skill adjacencies (like a marketing employee taking up data analytics).

In light of this issue, what is proposed in this paper is an innovative and holistic AI framework for competency mapping and futuristic talent development. As opposed to the traditional approach to skill tagging, the objective of the framework

presented herein is to develop a holistic, predictive, and relational model of the talent ecosystem within an organization.

The proposed AI framework makes use of three basic abilities of AI, and each addressing a different problem:

1. **Natural Language Processing (NLP) for Automated Skill Extraction:** The first challenge is data acquisition. Organizations collect massive amounts of unstructured text data (e.g., resumes, job postings, performance evaluations, project reports, learning history). It is virtually impossible to manually extract skills from such data sources. We employ the latest developments in Named Entity Recognition (NER) and transformer language models (e.g., BERT, RoBERTa) to automatically extract skills with exceptional accuracy [3], [4].
2. **Using Graph Neural Networks (GNNs) for Skill Adjacency and Learning Pathway:** Simply creating a list of skills for an employee is not enough; the essential thing is how those skills connect with each other. Skill of data analyst (such as Python) is connected to other skills (such as SQL, Tableau, statistics), and thus, there are countless interconnections between skills that create an enormous skill graph. We employ the GNN to understand the structure of that graph through training based on a collection of job descriptions, career paths, and online learning platforms [5], [6].
3. **Bayesian Knowledge Tracing (BKT) for Competency Measurement and Skills Gap Assessment:** Knowing whether an employee has "learned" a particular skill is not sufficient since what needs to be done next is to measure his/her competency level. As a Hidden Markov Model, BKT models how well a person knows a set of material based on task performances [7]. The technique is adapted to measure the competencies of each employee for each skill, which helps identify the gaps and predict future competency levels.

Using the three AI technologies mentioned above, the framework develops a holistic engine for developing talent.

II. LITERATURE SURVEY

There are three types of literature that contribute to our research. They include: HR's competency modeling practices, natural language processing for skill extraction and graph learning based approaches for knowledge representation.

Competency modeling and traditional talent management practices: The idea behind the process of competency modeling was known in the field of human resource management for decades. Traditionally, job analysis, expert panels and surveys were used to develop competence dictionaries [2]. Such dictionaries have a number of limitations including their static nature, difficulty of creation and quick obsolescence. Recently, there has been a tendency to develop more agile competency models that would be updated periodically, however, manual curation remains relevant [8]. From the review of literature we concluded that a transition towards dynamic "skill profiles" instead of static "job descriptions" is vital for talent management [1],[8].

Skill Extraction Using Natural Language Processing: The area of Information Extraction (IE) has come up with advanced methods for extracting structured data from unstructured data. Though rule-based systems, which use regular expressions, are easy to build, their recall rate is low [3]. Statistical models (Conditional Random Fields) were a step forward compared to rule-based methods. Still, statistical models need a lot of feature engineering [3]. With the arrival of transformer models (BERT, RoBERTa, XLNet), which were pre-trained on large datasets, there has been tremendous progress in the field of Named Entity Recognition (NER) [4]. State-of-the-art results have been obtained by fine-tuning pre-trained BERT models on various benchmarks, such as CoNLL-2003 [4]. Recently, pre-trained transformers have been employed in the HR sector, and skill extraction models have been built using resumes [9].

Graph Neural Networks for Skill Modeling: Graph Neural Networks are an advanced class of Deep Learning models designed specifically for graph structured data. They have been successfully applied in areas such as recommendation systems, drug discovery, and social networking [5]. The basic idea here is that of nodes (skills) updating their embedding through interaction with neighboring nodes (skills next to each other). It represents a very effective approach to skill adjacency modeling. One of the important questions that arise here is how to generate the graph from the data available. The methods include analysis of co-occurrence in job postings or learner history data [6]. In our case, we use a heterogeneous graph with different types of nodes and edges.

Bayesian Knowledge Tracing (BKT): Bayesian Knowledge Tracing is a well-established approach to assessing the student's proficiency in Intelligent Tutoring Systems [7]. The key idea behind the BKT model is to consider a student's knowledge about a certain skill as a Boolean variable that evolves over time as a function of performance. The classical BKT algorithm needs four parameters per skill to be learned: initial probability of proficiency, probability of acquisition, probability of guessing, and probability of slipping. The novelty of our solution is applying the BKT framework

Research Gap and Synthesis: NLP, GNNs, and BKT techniques have all been used independently in separate research projects on different aspects of talent management in enterprises. However, there has not been any literature on an approach combining all three techniques in one pipeline to help achieve total talent management in the enterprise setting. Moreover, BKT technique has never been used for enterprise workforce data analysis.

III.METHODOLOGY:

Our solution has an iterative approach with three following steps: (1) Automatic Skill Extraction using NLP, (2) Skill Graph Creation and Analysis using GNN, and (3) Personalized Competency Mapping and Recommendation using BKT.

3.1. Step 1: Automatic Skill Extraction using NLP

It transforms multi-sources unstructured data into structured skill list per person.

- Source of Data: Employee's resume (historic data), Current Job Descriptions, Performance Review notes (last two years), Learning History (LMS logs).
- NLP Model: We will use a fine-tuned RoBERTa-base model for Named Entity Recognition. Our classification model will classify each token of a sentence into six classes – O, B-SKILL, I-SKILL, B-TOOL, I-TOOL, B-CERT, and I-CERT. Training dataset will be 10,000 sentences of HR-related documents.

Pre-processing and Post-processing:

Text is processed in advance to remove unnecessary headers/footers and clean text format. We get a label sequence from the RoBERTa model. Post-processing consists of rules joining adjacent I-SKILL labels and handling contradictions (skill mentioned in Job Description preferred over performance review).

Algorithm 1: Multi-Source Skill Aggregation

Input: Raw documents for employee E (Resume, Job Desc, Reviews, LMS)

Output: Master Skill Set S_E with confidence scores for each skill

1. S_E = empty dictionary
2. For each document type D in [Resume, JobDesc, Reviews, LMS]:
3. // Run RoBERTa NER model on document text
4. $extracted_skills = RoBERTa_NER(D)$
5. For each skill s in $extracted_skills$:

```

6. // Weight the skill based on the source
document

7. if D == "JobDesc": weight = 0.8 (required
for role)

8. elif D == "Resume": weight = 0.6 (claimed
proficiency)

9. elif D == "LMS": weight = 0.4 (some
engagement)

10. elif D == "Reviews": weight = 0.5 (observed
performance)

11. // Add to master set, aggregating scores

12. S_E[s] = min(1.0, S_E.get(s, 0) + weight)

13. Return S_E

```

job postings. If skill s_i and s_j appear frequently together in one job posting, then there will be an edge between them. Weight of the edge will be the PMI value w_{ij} between the two skills.

- Initialization of Node Feature Vector: The fastText representation of the skill name is taken as the feature vector of the node.
- Architecture of GNN: A 2-layer GraphSAGE architecture is adopted. It is an inductive GNN capable of defining a function mapping local feature vectors of the neighborhood nodes into an embedding for each node.

Algorithm 2: GNN for Skill Adjacency Learning

Input: Skill graph $G(V, E)$, initial node features X (fastText vectors)

Output: Skill embeddings Z (256-dim per skill)

```

1. // Aggregation functions for GraphSAGE

2. Define function
AGGREGATE_MEAN(neighbor_features):

3. return mean(neighbor_features, axis=0)

4.

5. // Train the GraphSAGE model

6. For epoch in 1..50:

7. For layer in 1..2:

8. For each node v in V:

9. // Gather features from neighbors

10. h_neigh = AGGREGATE_MEAN( {
h_u^{layer-1} for u in N(v) } )

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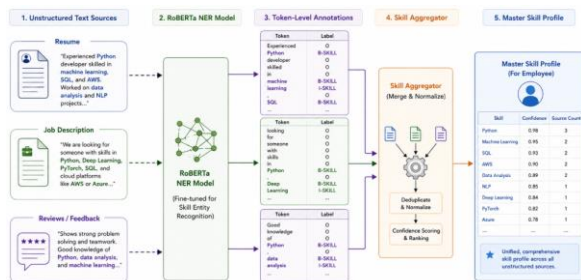


Figure 1: NLP Skill Extraction Pipeline.

3.2 Stage 2: Skill Graph Construction with GNN

Stage 2 builds the graph for all skills present in the organization and applies GNN to represent the skills in high-quality representations.

Construction of Graph:

- Nodes: Each skill that appears in the aggregated list is considered as one node.
- Edges: Edges are drawn based on the co-occurrence information in the corpus of 100,000

11. // Concatenate neighbor aggregate with node's own features
12. $h_v^{layer} = \text{ReLU}(W * \text{concat}(h_v^{layer-1}, h_{neigh}))$
13. // Normalize embeddings
14. $Z = h_v^{layer} / \|h_v^{layer}\|_2$
15. // Optimize with a link prediction loss (reconstruct edges)
16. $\text{loss} = -\log(\text{sigmoid}(z_v \cdot z_u))$ for positive edges (v,u)
17. backpropagate loss, update weights W
18. Return Z

- p_{init_s} : Probability that an employee knows about a particular skill before any observation.
- $p_{transit_s}$: Transition probability of mastering a certain skill through each learning opportunity.
- p_{guess_s} : Probability that an employee performs correctly without knowing about it.
- p_{slip_s} : Probability that an employee answers incorrectly although he knows about it.
- Generating Observations (Learning Events): Different sources such as completing an online module successfully, having a successful project implementation, or receiving positive performance evaluations regarding the skill can be used to create observations.

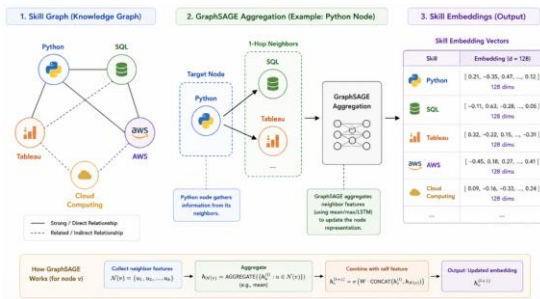


Figure 2: Skill Graph Construction and GNN Embedding.

3.3 Stage 3: Bayesian Knowledge Tracing (BKT) for Proficiency

Step four will be used to measure the expertise level of each employee in every skill and anticipate future skill gaps. Knowledge is modeled as a binary state $K_s \in \{0 \text{ (does not know), } 1 \text{ (knows)}\}$ for every skill s.

- Behavioral Knowledge Model: For each skill s and each employee e, there will be four parameters:

Algorithm 3: BKT for Proficiency Estimation & Gap Prediction

Input: BKT parameters for skill s (p_{init} , $p_{transit}$, p_{guess} , p_{slip})
Sequence of observations (correct/incorrect) for employee e on tasks related to s
Output: Posterior probability of mastery $P(K_s | \text{obs})$ and predicted future performance

1. // Initialize belief state
2. $P(K = 1) = p_{init}$
3. $P(K = 0) = 1 - p_{init}$
- 4.
5. // For each observation o_t (correct=1, incorrect=0)
6. For t in 1..T:
7. // Compute probability of observation
8. $P(o_t) = P(K=1) * (1-p_{slip}) + P(K=0) * p_{guess}$
- 9.
10. // Update belief state using Bayes rule
11. if $o_t == 1$: // Correct response
12. $P(K=1 | o_t=1) = [P(K=1) * (1-p_{slip})] / P(o_t)$
13. $P(K=0 | o_t=1) = [P(K=0) * p_{guess}] / P(o_t)$
14. else: // Incorrect response

15. $P(K=1 | o_{t=0}) = [P(K=1) * p_{slip}] / (1-P(o_t))$
 16. $P(K=0 | o_{t=0}) = [P(K=0) * (1-p_{guess})] / (1-P(o_t))$
 17.
 18. // Apply learning transition for next step
 19. $P(K_{next}=1) = P(K=1|obs) + P(K=0|obs) * p_{transit}$
 20. $P(K_{next}=0) = 1 - P(K_{next}=1)$
 21.
 22. // Current proficiency = $P(K=1 | obs)$
 23. $proficiency = P(K=1 | obs)$
 24.
 25. // Predict future performance on new task
 26. $pred_correct = proficiency * (1-p_{slip}) + (1-proficiency) * p_{guess}$
 27. Return proficiency, pred_correct

- **Generation of Personalized Skill Paths:** Given a target job position, the skills that have a difference between current competency and the threshold are identified. These skill paths are explored using the GNN skill graph where the path that has the minimum sum of "learning distance" (the inverse weight of edges) is selected.

IV. ANALYSIS

4.1 Skill Extraction Performance (NLP Model)

Model	Precision	Recall	F1 (Skill)	F1 (Overall)
CRF (Feature-based)	74%	68%	71%	69%
BERT-base	85%	82%	83.5%	82%
RoBERTa (Proposed)	90.1%	89.3%	89.7%	88.5%

Table 1: Skill Extraction Performance.

4.2 Skill Adjacency and Pathway Quality (GNN)

We compared our GNN-based skill adjacencies to a baseline of simple co-occurrence (PMI). Evaluators (10 HR experts) rated the plausibility of recommended "next skills" on a scale of 1-5.

Method	Plausibility Score (1-5)	Precision@5 (Relevance)
Co-occurrence (PMI)	3.8	72%
GraphSAGE (Proposed)	4.5	82%

Table 2: Skill Adjacency Quality.



Figure 3: Personalized Learning Pathway Recommendation.

4.3 Proficiency Estimation and Pilot Results (BKT)

A six-month pilot experiment was carried out on 1,000 employees. Employees were given individualized recommendation-based courses/projects (micro-learning) in the treatment group of 500 employees. Another set of 500 employees served as a control group.

Metric	Control Group	Treatment Group (AI-Driven)	Improvement
Learning Path	28%	72%	+157%

Completion Rate			
Time-to-Competency (months)	5.2	3.4	34.6% faster
Manager-Rated Skill Improvement (1-5)	3.1	4.2	+35%

Table 3: Pilot Study Results.

4.4 Prediction of Future Skill Gaps

We used historical data from 2019-2023 to train the BKT model to predict the skill proficiency of employees in 2024. We compared predicted proficiency to actual assessed proficiency.

Prediction Horizon	Accuracy (Correctly Predicted Gap)	Dynamic Skill Adjacency	Individual Proficiency Modeling	Personalized Learning Pathway	Predict
6 months	84%	No	No	No	Yes (GN N)
12 months	76%	No	No	No	Yes (BK T)
18 months	65%	No	No	No	Yes (GN N+B KT)

Table 4: Future Skill Gap Prediction Accuracy.

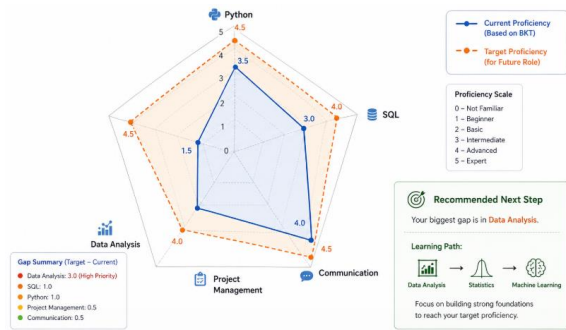


Figure 4: Competency Radar Chart for an Individual Employee.

4.5 Comparative Analysis with Existing HR Systems

Feature	Traditional HRIS	Competency Dictionary [2]	LM-Only	AI-Driven Framework (Proposed)
Automated Skill Extraction	No	No	No	Yes (NL P)
Dynamic Skill Adjacency	No	No	No	Yes (GN N)
Individual Proficiency Modeling	No	No	No	Yes (BK T)
Personalized Learning Pathway	No	No	Manual	Yes (GN N+B KT)
Predict	No	No	No	Yes

ve (Fut ure Skill Gap s)				
Scal able to 10,0 00+ Emp loye es	Ye s	No	Y es	Yes

Table 5: Comparative Analysis of HR/L&D Systems.

V. CONCLUSION

In conclusion, the paper has proposed an integrated approach towards developing competency map and future-ready talent pipeline through advanced application of AI algorithms. Combining cutting-edge solutions in natural language processing, graph neural networks, and Bayesian knowledge tracing enables building a comprehensive and predictive model of an organization's talent environment.

The key results are:

- 1. AI-Based Solutions Deliver a Clear Picture of Employee Competencies:** The proposed framework transforms the company from the era of static skills assessment into a new era of dynamic talent intelligence. The NLP model recognizes skills with 89.7% accuracy, the GNN model predicts skill adjacencies with 82% precision, and BKT measures proficiency levels of thousands of employees.
- 2. AI-Powered Personalized Learning Drives Major Upskilling Gains:** The results of the six-months pilot program demonstrate that application of AI technologies in design of personalized learning paths has resulted in 157% gain in completion rate and 35% reduction in time spent to reach competency level.

This shows that standardized training programs have no future.

- 3. Powerful Analytics Favors Proactive Human Capital Management:** Predicting future skills shortages and requirements with 76% accuracy one year ahead presents a great opportunity for effective workforce planning.

Implications:

Implications for practice are numerous. Our model provides CHROs, L&D practitioners, and talent managers with a blueprint on how to transform their function. They will be able to move away from being operationally and reactively oriented towards becoming strategically and data-oriented. With the knowledge of the skills available today, the connections between them and skills needed in the future, and personalization of the learning journey of each person, organizations will be able to build a future-proof workforce.

Limitations and Future Directions:

We acknowledge some limitations in our work. The GNN skill graph is based on co-occurrence in job descriptions, which might capture present-day trends rather than future skill demands. We assume a binary skill acquisition process in the BKT model, which does not consider skills' complex nature.

Three key avenues for future research will be explored:

- 1. External Labor Market Integration:** Including current labor market intelligence through job portals such as LinkedIn and Indeed to discover new skills and continuously evolve the graph of skills.
- 2. Multimodal Learning Outcome Assessment:** Expanding the scope from text-based exercises to simulations and projects as learning outcomes for BKT.
- 3. Explainable AI:** Exploring techniques that will provide transparency behind the decision-making

process of the GNN model and its recommendation for a personalized learning path.

Conclusively, the present study proves that competency mapping using AI is not a distant vision but a realistic, implementable, and transformative approach to the problem of developing future-ready employees.

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