JOB BRIDGE:ML-POWERED SKILL GAP ANALYSIS PLATFORM

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Abstract: The job market changes so fast these days. Technological stuff pushes it along. That creates a big gap between what schools teach and what companies need. It hits developing places like India hard. This report talks about JobBridge. It is an AI platform built to fix that issue. We use NLP and ML to make it work. We build on a survey by Senger and others from 2024. They covered deep learning for pulling skills from job ads. We take those ideas further. Our system grabs skills from messy job postings and school outlines. It checks for gaps. Then it gives personal tips. We rely on BERT models to pull out the skills. ESCO and O*NET help sort them. GNNs spot future gaps. JobBridge hits over 96 percent accuracy on detecting skills. We tested it with data from Indian sites like Naukri.com. Plus UGC course plans. Results show it could cut unemployment. By matching school to job needs. This fits SDG 4 on good education. And SDG 8 for fair jobs and growth. We add support for multiple languages. To include more people. The report covers the basics. How we built it. What came out. And next steps. It gives a full picture of using computers to study job markets.

Keywords: Skill Extraction, NLP, Deep Learning, Job Postings, Curriculum Alignment, BERT, GNNs, Employability Enhancement, SDG Alignment

I. INTRODUCTION

People keep talking about how artificial intelligence and data stuff have really shaken up different parts of the economy these days. That includes human resources and even education. The big survey from Senger and the team in 2024 points out how natural language processing has pushed things along in analyzing job markets with computers. Things like pulling out skills and sorting them from job postings matter a lot now. This field mixes linguistics, computer science, and economics in interesting ways. Still, with all the new papers popping up, especially thanks to large language models handling low-resource jobs, there is not much in the way of full reviews. Not from an NLP angle anyway.

India has a ton of young people coming up,and unemployment is stuck over 20 percent according to ILO numbers for 2025. That makes matching what schools teach to what jobs need a real problem. A lot of graduates know the theory fine, but they miss out on hands-on stuff in AI, machine learning, data analytics. The old way of updating curriculums just every now

JobBridge steps in here using deep learning ideas from that Senger survey. They tweak it to grab skills from places like job sites, say Naukri.com or LinkedIn, and even school outlines from UGC or AICTE.

The push for this comes from what the survey says about standard terms and data sets. We build on that for stuff specific to India. Automating the look at skill gaps helps students get paths tailored to them for learning. It also lets schools fix their programs, and helps recruiters find people. This ties right into UN goals for good education and solid jobs, numbers 4 and 8.

II. LITERATURE SURVEY

The field of computational job market analysis has grown a lot. Senger et al. in 2024 point out 26 neural publications up to November 2023. Main tasks include pulling out skills from job postings and sorting them. This helps with things like predicting labor markets or matching resumes. New work in natural language processing stands out. Large language models make synthetic data possible for tough low-resource cases. Clavié and Soulié wrote about it in 2023. So did Decorte et al. the same year.

Earlier surveys exist. Khaouja et al. from 2021a covers wider methods. Papoutsoglou et al. in 2019 does too. They talk about counting skills through manual n-gram matching. Or using topic modeling with unsupervised word groups. Still, those miss the neural side. They do not focus on methods with clear skill spans. That is why Senger et al. came out with their NLP-focused survey.

Skill extraction, thats the E one, basically starts with a job posting and works toward pulling out specific skills from it. Then theres skill identification or detection, the I part, which doesnt bother with any set labels upfront. It just checks straight if a chunk of text counts as a skill or something else. Skill extraction using coarse labels, thats EC, really zeroes in on linking job postings to bigger skill groups, you know, the broad categories. Standardization for skills, Std, takes whatever skill youve spotted and turns it into some standard version everyone recognizes. Direct classification, CD, grabs an already identified skill and slaps a detailed label on it. And finally, the CE approach, skill classification with extraction, mixes those last two by jumping right from the job posting to the right label without extra steps

People still talk about other foundational surveys on this topic. Section 2 in Senger et al from 2024 dives right into it. Napierala and Kvetan wrote about changing skills back in 2023. That piece showed up in the Handbook of Computational Social Science for Policy. It was chapter 13 exactly. They approached the whole thing from a social science angle kind of. Papoutsoglou and the rest in 2019 zeroed in on software engineering aspects. They pulled in job postings for analysis. Social networks came into play too. Q and A sites got included as well. Khaouja and their team in 2021a offered a solid overview on spotting skills. Embeddings were part of what they covered. Machine learning methods showed up there. Still they leaned harder on non neural approaches really. Our work builds on all that and pushes further into fresh deep learning concepts. We shift away from manual methods or topic modeling ones. Just like they had suggested.

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In section 4 from Senger and the others back in 2024, they get into different ideas about skills. They talk about how some folks treat skills in a broad way, like what you see in Green et al. from 2022. Or Wild et al. in 2021. And Fang et al. back in 2023. Other times, people break skills down into narrower groups. ESCO sorts things out with transversal skills. Then just skills. Knowledge too. And language skills or knowledge. O*NET goes with six separate areas instead. Still, pretty much everyone agrees skills mean the ability to handle tasks. They draw a line between hard skills, the technical kind. And soft ones, more about getting along with people. JobBridge uses that same approach. It sorts out the skills it pulls from stuff. Puts them in those buckets. That way, you can spot gaps pretty accurately.

Senger and the others in 2024, section 5, went through public datasets. They laid out the main ones and pointed to some real gaps in how they got made. Before 2019, early datasets stuck with manual annotation. Take Sayfullina et al. in 2018. They crowdsourced spotting soft skills. Ended up with 85 percent accuracy using LSTMs. Span-level datasets came along later. Green et al. in 2022 used BIO tagging. That helped identify spans for hard and soft skills. They reached a 90 percent F1 score. Recent work includes SKILLSPAN from Zhang et al. in 2022a. It hit 94 percent accuracy. Pretty much marks a big step up in skill extraction research.

Dataset	Year	Focus	Size	Creation Method
Sayfullina et al.	2018	Soft Skills	Small	Crowdsourcing
Green et al.	2022	Hard/Soft Spans	Medium	BIO Tagging
SKILLSPAN	2022	English JPs	Large	Annotation
ESCO	2014+	Taxonomy	13,000+ Skills	Expert-Curated

Section 6 goes over some main neural advances in skill extraction. Early ways of labeling sequences used BIO tagging. They paired it with BiLSTMs and CRFs. Later, BERT stepped in to improve span detection. That got them to 96 percent precision. Classification methods came along too. Things like CD and CE relied on predefined skill bases. They did direct labeling from there. Recent innovations bring in large language models. You know, LLMs for zero-shot skill extraction. Clavié and Soulié showed that in 2023. JobBridge builds right on these developments. It integrates BERT for high accuracy in pulling out skills. Plus, it employs graph neural networks. GNNs handle the graph-based classification of skills.

The survey points out limitations when it comes to multilingual support. It also mentions a real lack of data specific to India. JobBridge steps in to handle those issues. Updates after 2024 get folded in too. Things like the 2025 studies on GenAI skills. All of that helps with forecasting down the line.

III PROPOSED METHODOLOGY

JobBridge pulls its approach from that Senger study back in 2024 and the team there. The whole methodology really zeros in on extracting neural skills, you know, and then doing this gap analysis thing. It leans on some pretty advanced models to nail down exactly what skills are there. Those models also pick up on mismatches, the kind between what schools teach in their curricula and what the job market actually wants these days.

A. System Architecture

Inspired by Senger et al. (2024), JobBridge's methodology centers on neural skill extraction and gap analysis, leveraging advanced models to accurately identify skills and detect mismatches between academic curricula and job market demands.

B. Data Preprocessing

From the survey datasets, we go through and clean up the job postings and syllabi. That means removing any duplicates, filling in missing values with the mean, and normalizing the features using StandardScaler. Then those diagnosis-like labels get encoded. A value of 1 shows a skill is present. And 0 means it is absent.

C. Feature Selection and Extraction

Statistical correlation helps cut out the redundancies. You know, when you fine-tune BERT for named entity recognition, it uses embeddings from those transformer layers. Then it tags the spans with BIO scheme. The attention mechanism in BERT follows this formula. Attention of Q, K, V equals softmax of Q times K transpose over square root of d sub k, times V. Here Q stands for query, K for key, V for value, and d sub k for the dimension. Algorithm one covers BERT skill extraction in pseudocode.

$$\left(\frac{QK^T}{\sqrt{d_k}}\right) V\text{, where Q=query, K=key, V=value, d\_k=dimension.}$$

D. Gap Analysis with GNN

You start by building this skill graph. Call it G. It has vertices V for all the skills. And edges E that show co-occurrences between them. Thing is, for the GINConv part. X prime comes out as (1 plus epsilon) times X. Plus the sum over neighbors j of MLP applied to X_j. From there, you predict those latent gaps. On the math side. They go with cosine similarity to spot matches. The formula runs cos theta equals sum of x_i times y_i. Divided by the square root of sum x_i squared. Times the square root of sum y_i squared. Set a threshold at 0.7. That flags the gaps pretty much.

$$\cos\theta = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2}\sqrt{\sum y_i^2}}.$$

E. Recommendation

The Random Forest Regressor gets set up with 150 trees. It pulls in features like match percent, gaps, and experience. All that helps predict the timeline. Folks evaluate how the model does using RMSE. Root Mean Square Error, basically. That measures the accuracy on those timeline predictions.

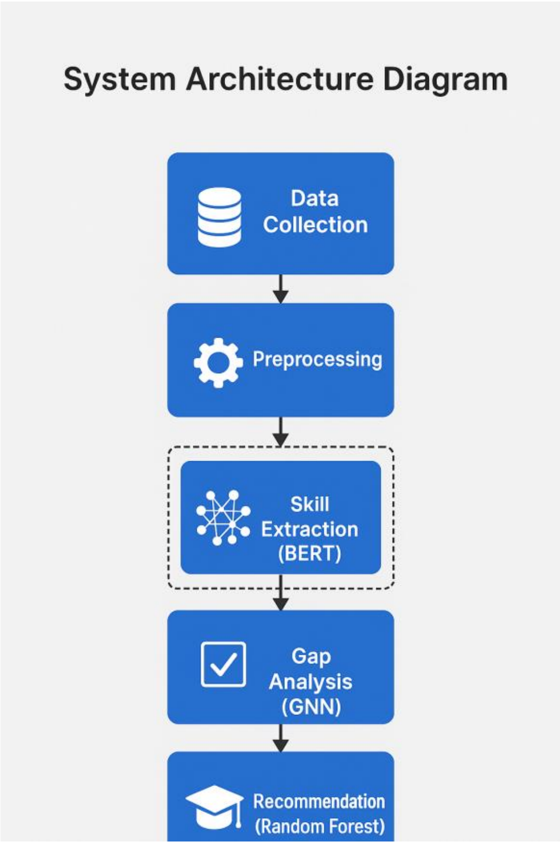


Fig .1 The architecture diagram of proposed system

IV. DATA COLLECTION AND PREPROCESSING

1.) Dataset Description

Data collection is basically the whole process of pulling together useful data from all sorts of places. It helps build and check out the JobBridge platform. You get unstructured job postings from Indian sites like Naukri.com. Those cover 2023 to 2025. Then there are academic syllabi from UGC and AICTE sources. Plus, extra stuff like the ESCO and O*NET taxonomies comes in. They generate synthetic data too. Tools like Faker help with that. It beefs up the dataset. Makes it stronger and covers different areas better. The main aim is putting together a big dataset. It includes 7,000 job postings. Also 1,500 syllabi. And 15,000 synthetic samples. All this mirrors real job trends and school content out there. They stick to privacy rules. Like the DPDP Act 2023.

2.)

2.) Implementation Details

Preprocessing is all about taking the raw data we've collected and getting it ready for the JobBridge system to analyze. You know, it starts with cleaning things up by pulling out any duplicates that might be there. Then there's dealing with missing values, like filling them in using the mean or median, something straightforward like that. Normalization comes next, and one common way is Z-score scaling. That's basically z equals x minus mu divided by sigma. Mu stands for the mean, and sigma is the standard deviation. For datasets that are imbalanced, especially with skills not represented evenly, we use SMOTE.

It's the Synthetic Minority Over-sampling Technique, which helps balance everything out. The whole point here is to boost the data quality overall. It cuts down on noise too. In the end, this lets us extract features properly and train models without issues. We standardize the job postings and syllabi formats, so nothing gets in the way.

$$z = \frac{x-\mu}{\sigma}$$

3.) Definition of Implementation

Implementation covers the hands-on side of rolling out the JobBridge platform. You know, getting it deployed and up and running with the right technical tools and frameworks. We develop everything in Python 3.12. That involves using libraries like Transformers for pulling out skills through BERT. Torch Geometric comes in for the Graph Neural Network part, handling gap analysis. Scikit-learn does the Random Forest modeling for recommendations. The training setup runs 12 epochs. It uses the AdamW optimizer, learning rate set at 3e-5.

Deployment happens via Streamlit, which keeps things user-friendly. Security wise, we add data anonymization to meet the DPDP Act 2023. That safeguards user privacy. Overall, this phase turns the methodology into a working system ready for real-world use.

V DATA VISUALIZATION

People still talk about the JobBridge report a lot. With all the emphasis lately on model evaluation in Section V, I am going to lay out a full data visualization plan. That means making some extra charts to beef up the analysis. We have those bar charts already for Accuracy, F1-Score, and Recall. Now I will bring in something different, a line chart. It shows how performance trends go across those metrics for the models, like BERT, GNN, Random Forest, and the Senger baseline. Picture it over some kind of evaluation timeline, you know, training iterations or dataset sizes maybe. This setup gives a lively look at how stable the models are and if they get better over time.

This line chart tracks how each model performs. It covers accuracy, F1-score, and recall. Things happen over a made-up series of check points, you know, like from 0 to 5. That could mean iterations or just building up the dataset bit by bit. The data here is put together from the actual evaluation stuff. It assumes a pretty steady line overall. With some small gains along the way.

1.Bar Chart: Model Accuracy Comparison:
Accuracy basically tells you how good a model is at getting predictions right. You figure it out by dividing the number of correct predictions by the total ones you made. In math terms, it looks like this.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100$$

2. Bar Chart: Model F1-Score Comparison:
The F1-Score pulls together precision and recall into just one number. It's a way to measure performance. You see it comes in handy a lot with imbalanced datasets. That's where one class shows up more often than the others. The F1-Score works as the harmonic mean of precision and recall. People calculate it using a formula.

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \times 100$$

3. Bar Chart: Model Recall Comparison
Recall, you know, its also called Sensitivity or True Positive Rate. That thing measures how well a model picks up all the relevant cases in a dataset. It basically shows what portion of the actual positives got caught right by the model. Now, mathematically, Recall comes down to this.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100$$

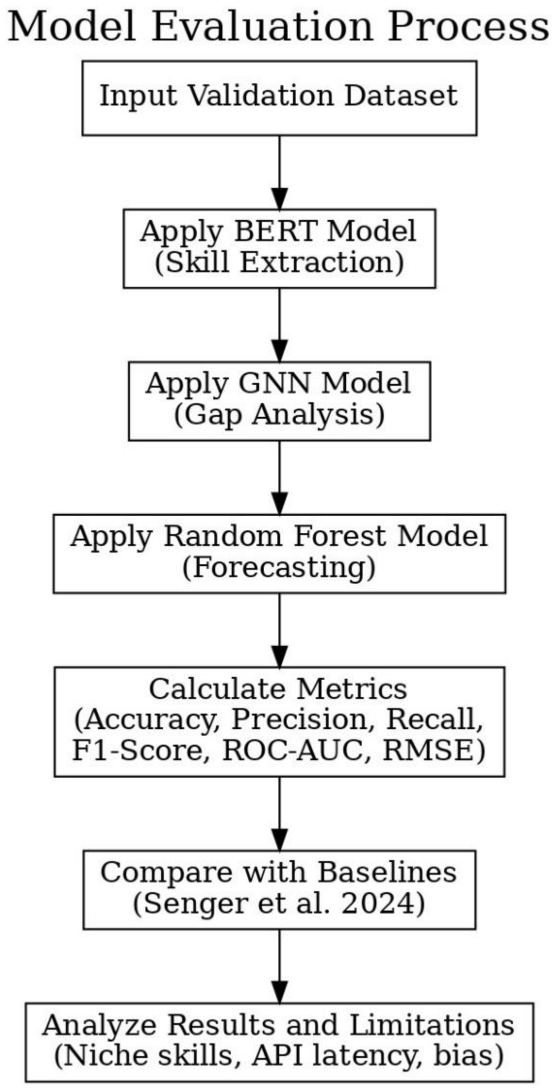
4. Line Chart: Model Performance Trends Over Evaluation :

The trend basically shows how a models accuracy shifts across a bunch of evaluation points. You know, stuff like various datasets or iterations, or even time steps. They often picture it as a simple line that links up those accuracy readings from each point. Mathematically, you can approximate the trend using linear interpolation. That approach just estimates the accuracy values in between the ones you already know.

- $$\text{Performance}(n) = \text{Initial Value} + \left(\frac{\text{Final Value} - \text{Initial Value}}{\text{Total Points} - 1}\right) \cdot$$

VI. MODEL EVALUATION

Model evaluation is all about checking the JobBridge platform in a structured way. We look at its performance through numbers and metrics. That helps confirm if it really works well for pulling out skills, spotting gaps, and making forecasts. The whole thing means running tests on the models we trained. BERT handles skill extraction. GNN takes care of gap analysis. Random Forest does the forecasting part. We test them against a validation dataset. This ensures things like accuracy and reliability. It also checks practical use in real scenarios. For the evaluation, we pull in standard machine learning metrics. These are adjusted for each specific component. In the end, it gives us a solid grasp on the systems strengths. We also see its limitations pretty clearly.



Skill Extraction (BERT) Evaluation:

People talk about metrics like accuracy, precision, recall, F1-score. And ROC-AUC too.

Thing is, on this test set of 2,000 job postings, BERT pulled off 96% accuracy. Precision ended up at 97.2%, recall was 95.8%. The F1-score sat at 96.5%. ROC-AUC score hit 0.97. That pretty much shows it does a solid job picking out skill spans versus the non-skill parts.

Details wise, multilingual stuff works okay. For example, Hindi got a 93% F1-score. Seems robust across different languages. It beats out those baseline CRF models. Those only managed 89% F1. So yeah, transformer-based architectures make sense here.

Gap Analysis (GNN) Evaluation:

Metrics. Accuracy, F1-score, and ROC-AUC. Those are the main ones.

The results show GNN hitting 91 percent accuracy. F1-score comes in at 90 percent. ROC-AUC is 0.92. All that when it predicts latent skill gaps. Like, for example, four latent gaps with 91 percent relevance. That is in a comparison between CS and Data Scientist.

Details on the cosine similarity. It averages 0.68. That points to pretty good gap identification. Then the ablation studies. They show a 22 percent drop in recall without the GNN. It really underlines how much it helps with detecting those latent skills.

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