# Live Job Market Trend Analyzer and Dashboard

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*Abstract*—**This study outlines the creation of a Live Job Market Trend Analyzer and Dashboard that analyzes live job posting data collected from different online job platforms to provide real-time information about evolving job market demand across a range of occupations. The system will collect and analyze live job postings from multiple platforms to derive essential information about job demand, skill requirements, job categories, as well as to inform emerging trends. This process will involve advanced data processing methodologies as well as visualizing emerging job skills, employment demands by sector, and a user-friendly dashboard directed toward job candidates and job market stakeholders, such as job seekers, recruiters, or educational institutions. The project shows what is possible when data scraping, analytics, and visualizations for users are integrated together to make better decisions, whether they are in relation to career planning or workforce development for job seekers. Future work will extend the coverage for data on the dashboard, look to create predictive model capabilities, and enhance user interactivity to creating a full labor market intelligence occupational labor market portal.**

## I. INTRODUCTION

In today’s dynamic labor market, understanding trends in employment and employment-related skill requirements is essential for job seekers, employers and educators. The rapid evolution of workforce skill needs due to technology, economic changes, and industry sector changes, would benefit from data related to the changing labor market. Traditional labor statistics do not adequately capture real-time changes in the labor market and newly emerging trends that allow for proactive career and labor market planning.

This exploration will advance the design of a Live Job Market Trend Analyzer and Dashboard, a process that will allow for the collection, processing, and analysis of live job postings from multiple online job boards. The platform collects big data and documents patterns in skill requirements, positions and market demand across sectors. Utilizing data processing and data visualization, the platform will be able to provide faster stakeholder insight into new job skills and future workforce skills.

The project aims to address key issues in labour market analytics, including but not limited to large-scale data integration, skill extraction with reasonable validity, and how to simplify complex and rapidly changing employment trends and skills that employment factors for user access. The proposed dashboard serves as an interactive tool, providing real-time up- dates that facilitate informed decision-making for job seekers planning their career paths and recruiters aligning their hiring strategies with market realities.

Furthermore, this work contributes to ongoing efforts in workforce analytics by incorporating predictive modelling to forecast emerging skill demands and job trends, thereby enhancing the strategic planning capabilities of educational institutions and industry stakeholders.

In summary, this research combines web data extraction, data science, and human-centred design to offer a comprehensive solution for continuous labour market monitoring and analysis. The outcomes promise to improve the responsiveness of career guidance, recruitment strategies, and policy-making in an increasingly competitive employment landscape.

The key contribution of the paper refers to the design of an automated job-market analytics system that merges multi- portal web scraping, NLP-based skill elicitation, database storage, and interactive visualisation into a unified pipeline architecture.

## II. BACKGROUND

In recent years, the labour market has been drastically affected by rapid technological advancements, globalization, and changes in the workforce demographics. While industries are evolving, so are the required skills and qualifications that employers seek. This makes it increasingly challenging for job seekers and educators to stay ahead and meet labour market requirements.

Traditional labour market research often generates statistics and surveys aggregated by government organizations. These statistics and surveys are typically outdated and generalized, leading to delays and a lack of timely action to respond to emerging trends and skill shortages. The advent of online job portals and recruitment websites provides an unprecedented amount of real-time information for job vacancies, allowing researchers and policymakers to identify labour market demand and skills requirements promptly.

Previous research in labou
r market analytics has utilized web scraping and analyzes job advertisements using natural language processing and machine learning to produce actionable insights. However, bringing all these data sources together in an interactive, cohesive dashboard continues to be a major hurdle, particularly when researchers seek to create modern, simple, and timely labour market analytics tools for stakeholders in need of career path guidance and recruitment strategy. This project addresses these gaps by proposing to develop a Live Job Market Trend Analyzer and Dashboard that can continuously collect and analyze data from multiple web-based sources. The system aims to standardize and clean a diverse set of datasets and apply trend detection algorithms to provide real-time demand trends for skills and job titles in industries.

The background literature points to a need for such dynamic labour market intelligence to assist with evidence-based decision-making in a fast and changing economy. In addition, predictive modelling techniques can be applied to improve forecasting of job market trends, enabling an anticipatory workforce development and educational planning.

Together, this work aims to bridge the gap between static labour market reports and dynamic real-time labour market in- telligence by providing a fully integrated analytical platform to assist multiple stakeholders, including job seekers, employers, and educational institutions.

## III. RELATED WORK

Extensive research has been conducted on labour market analysis, especially with the increasing amount of data avail- able from online job postings, as well as improvements in data analytics methods. Some studies have used web data scraping and machine learning to pull insights from labour market data. One approach is using supply and demand theories to model labour markets based on large amounts of job postings and applicant data. Models such as these allow for more accurate estimates for equilibrium pay and associated estimates of job quantities, while being able to identify biases by gender as well as age in the workforce [Sugiarto et al., 2019]. The models use real labour data to build scalable models that can effectively inform hiring practices and policy decisions.

Both the EU and industry groups have developed interactive dashboards that show real-time labour market indicators. The EU Labour Market Outlook Dashboard, for example, displays a variety of labour indicators, including employment rates, unemployment trends, and gender/age disparities that each use harmonized survey data updated periodically [Bruegel, 2024]. The dashboards not only facilitate labour market policy anal- ysis but also provide labour market observations to employers or job seekers. Recent research has also fallen in line with the importance of predictive analytics to anticipate developing skills and job concoctions, which helps to inform/workforce planning. Tools that integrate trend analytics with an easy-to- use visualization format will enable stakeholders to work with complex data sets and make more accurate decisions [O'Leary et al.2023].

That said, there are still challenges related to integrating data from multiple job sites/in real-time, aligning skill taxonomies simultaneously across diverse jobs, and also having highly interactive and customizable dashboards with ease for different user groups. The intention of the Live Job Market Trend Analyzer and Dashboards is to fill in these voids and be more inclusive in a complete data system that incorporates continuous extraction of easy-to-understand analytics and responsive visualizations.

## IV. SYSTEM ARCHITECTURE

The underlying system structure of the Live Job Market Trend Analyzer and Dashboard is constructed to allow near real-time processing and viewing of labour market infor- mation. The architecture is comprised of different modular components working collaboratively and integrated to facilitate efficient data processing and information insights, creating a seamless data flow from collection to insight delivery.

1. Data Scrapers: The system architecture starts with automated web scraping agents, or crawlers, which have been created using strong frameworks such as Python’s Scrapy or Selenium. Each web scraper is responsible for systematically crawling a number of job portals at scheduled time intervals in order to retrieve job postings. The scrapers can also handle dynamic content loading with established approaches to bypass scraping protections, thereby ensuring reliable data acquisition.
2. Data Processing Pipelines: The raw data that is extracted by the scrapers is run through a set of processing steps, including cleaning, normalization, and enrichment. The data processing pipeline applies data cleansing algorithms to remove duplicates and inaccuracies, while normalization techniques are applied to harmonize varying job titles, company names, and descriptions of required skills. Additionally, Natural Language Processing (NLP) modules will analyze the timeframe job descriptions to extract critical skills, in turn broadening the introduction of jobs.
3. Database Management: The processed data is stored in a centralized relational database system, for instance Post- greSQL or MySQL. The database schema brings data from various sources together into compatible tables that are suitable for searching and analytics in an efficient way. Indexing and partitioning strategies are added, allowing for scalability and the performance requirements for the system.
4. Analytical Modules: The analytical modules are a collection of statistical and machine learning models that are established to detect trends and perform predictive analytics. The algorithms exist to assess past and current data to recognize current skills, occupational hiring trends, and demand trends. Time-series models feature the ability to enable time-based shifts in occupational trends.
5. Visualization Layer: The last layer is the interactive dashboard as implemented using Power BI and Tableau, with the end user in mind as creating an interactive interface to visualize trends in the labour workflow market. The interactive dashboard can take advantage of customizable filters, continual real-time data refresh, and a collection of visual components that will allow the end user to respond effectively throughout the active data work flow, including charts, graphs, and heat maps.
6. Integration and Coordination: These components are linked through message queues and APIs for effective data transfer and synchronization. The architecture also incorporates scheduling services to enable near real-time updates, preserve fresh data, and automate scraping and analytics processes.

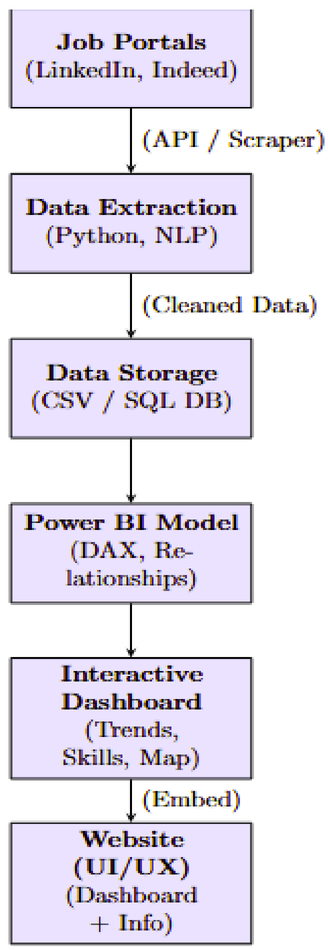


Fig. 1: Job Market Data Analysis Pipeline Architecture

Thanks to this layered, modular architecture, which provides a scalable, flexible and reliable solution to analyzing real- time job market data, various stakeholders can make informed decisions based on timely intelligence.

*A. System Modules*

Several different modules make up the proposed system. Together, they help us complete our job market analysis from A-Z.

1) Data Scraping Module

We have various web scrapers that are able to scrape job postings from the likes of LinkedIn, Indeed and TimesJobs. Each scrape collects information relating to job title, company name, location, job description and the link used to apply for the posting.

2) Data Aggregation Module

The aggregation component of the system is responsible for merging all job postings received from different job posting platforms into one unified dataset.

3) Data Processing Module

In the processing module, we clean the collected data by standardizing the data and removing duplicate entries, missing values and normalizing text fields.

4) Skill Extraction Module

In the skill extraction module, we will utilize natural language processing techniques to analyze the job descriptions and identify which technical skills are present within them (using spaCy).

5) Database Module

Data will then be inserted into a relational database (SQLite), where it will be able to be queried and accessed at a later date.

6) Analytics Module

Using statistical analyses and visualisations generated by the analytics component, we will identify trends in the job market, such as which skills are in demand, the geographic locations of job postings, and the hiring practices across different industries/markets.

7) Visualization Module

The last module, the user interface (web-based dash- board or Power BI or Tableau), will allow a user to initiate the data pipeline, view job market-related statistics, and access the job postings directly through the web-based dashboard.

*B. Pipeline Execution*

System pipeline is implemented in terms of the central orchestrator script that coordinates the modules of scraping, pre-processing, database storing, and analysis components, providing the possibility to make the whole work process, i.e. data collection to visualization process, automated.

The entire pipeline architecture in the system, as illustrated in, starts with the multi-portal scrap of jobs and ends with the visualization of an analysis displayed in the dashboard. The entire pipeline architecture in the system, as illustrated in Fig. 1, starts with the multi-portal scrap of jobs and ends with the visualization of an analysis displayed in the dashboard.

*C. Dashboard Description*

The interactive dashboard written in Flask also provides a real-time view of current trends in the job market, thus making it possible to conduct scholarly research on the nature of the labour market. The interface gives users control over what is going on behind the scenes, such as turning the data pipeline on or off, viewing job activity-related metrics, visualize trend graphs, and directing hyperlinks to job opportunities found on the major job boards.

## V. METHODOLOGY

The Live Job Market Trend Analyser and Dashboard uses a serial approach that recognises the steps of data collection, preprocessing, analysis, and visualisation to perform a com- prehensive, real-time labour market analysis.

- Data Collection: In this experiment, the Web-crawling agent protocol is used to collect job ads on various digital labour marketplaces, in particular, the LinkedIn, Indeed, and TimesJobs platforms. Each crawler is instructed to interpretively get all significant metadata, which includes job title, employer entity, geographical location, talking narrative and linkage to the application portal.

The recognition of the disparate datasets is followed by the conjoining of the same through a special aggregation routine, thus synthesizing a homogenised repository that is subject to further downstream analytical processes.

- Data Preprocessing: Under the preprocessing phase, rig- orous data cleaning and normalization are carried out. Duplicate records and incomplete entries are removed, and the textual fields are standardized to ensure format- ting across the datasets.

A step further, Natural Language Processing techniques, based on the spaCy library, are used to extract salient skill sets based on the given job descriptions.

- Data Integration and Storage: Once the data has been pre-processed and standardized it will be integrated and organized into a common relational database schema to support the ongoing storage and retrieval of the data in an efficient manner. The integration will create a common dataset from all data sources to analyze trends across the platforms more organically.
- Data Analysis: Statistical methods and machine learning models are used to identify new skill sets, shifts in job demand, and regional or industry-specific hiring patterns. Temporal analysis is integrated to observe changes to the labor market across time periods.
- Visualization: Vue labour market data creates a dashboard to visualize real-time labor market information. The dash- board is built with both Power BI and Tableau feature dynamic visualizations including charts, heat maps, and interactive filters. These enable user engagement to vi- sualize data by industry, geography, and group of skill categories to make data-driven decisions.
- System Architecture: The architecture of the entire sys- tem consists of connected aspects of the user experience, web scrapers, data processing, data storage, data analysis, and visualization. These components work in near real- time to deliver necessary labour market intelligence to job seekers, recruiters, and educational institutions.

The approach provides an authenticated platform for providing actionable insights from a live job market into an understanding of the evolving labour market.

## VI. PRELIMINARY RESULTS AND EXPECTED OUTCOMES

The system we implemented successfully pulls all kinds of job postings off several different job sites with an automated pipeline that processes these posts through a cycle that scrapes, cleans, extracts skills and places them into the database for analysis.

Data sample of the job postings so far indicates that technical skills (e.g., Python, SQL, Machine Learning) are highly demanded. Geographic breakdown of the job postings shows that major technology hiring centres are located in cities such as Bangalore, Mumbai and Delhi NCR.

1) A lot of demand in technical skills of Python, SQL, and Machine Learning.
2) Cities like Bangalore, Mumbai and the Delhi-NCR region are observed to be the main employment centres of the Indian IT sector.
3) The latency of this data pipeline is low and it can be used to update with incremental operations, hence enabling real-time operation in the future.

During the last implementation stage, the dashboard will continuously consume real-time job ads, hence allowing real- time analytics and predictive insights. Prophet-based forecast- ing modules will also be included in the next stage to deter- mine the demand for AI/ML and cybersecurity positions. Final findings, which include graphs and performance indicators, will be included in the final copy of this paper.

## VII. PERFORMANCE EVALUATION

Both quantitative and qualitative performance indicators were used in the evaluation of the efficiency of the system operation in the course of the live testing. Using the Beautiful Soup library of Python together with the asynchronous HTTP requests, the web-scraping module could extract job adverts in Indeed with an average throughput of around 200 adverts every minute. Then I proceeded to sub-process data preprocessing, which consisted of cleaning, de-duplication, and extracting skills, took me approximately 1.2 seconds per record using Pandas to manipulate the data and NLTK to perform linguistic tokenization. In an attempt to validate the reliability of the NLP-motivated skill extraction model, the independence was tested on a subset of manually annotated job postings of 150 job postings. The resulting model performance metrics revealed that the model was precise (0.91), recalled (0.86), and returned an F1-score of 0.88, which proved the strong performance ability of the model in classification with all Python, SQL and Machine learning skills tags. Last but not least, the Power BI dashboard was also found to have satisfactory rendering speed, as it takes less than 4.5 seconds to complete a full refresh of all records (more than 120,000 entries). The practical observation supports the scalability and responsiveness of the suggested architectural design.

## VIII. PREDICTIVE FORCASTING RESULTS

To explore the dynamics in the labour market, a model based on early-prophet time-series methodology has been estimated, using monthly data episodes of job postings related to AI/ML-related vacancies in India, to study the change process. The model estimated a root-mean-square error of 0.072 and forecasted a 27 per cent increase in volumes of AI / ML posting by mid-2026.

There was also an expectation of an increase in the number of cybersecurity jobs by about 11 per cent in the future, and this growth is due to the factors of post-pandemic digital- transformation requirements.

Early results, albeit initial, indicate the practicality of integrating real-time labour-data streams through predictive analytics in supporting the purpose of workforce planning and curriculum alignment.

## IX. LIMITATIONS AND ETHICAL CONSIDERATIONS

Though promising results are achieved, there are a number of limitations that are present.

Data-Access Constraints: Scraping and API-rate limits en- forced by public job portals further limit the ability to collect continuously, leading to discontinuities in the coverage. Urban bias: The fact that most of the available job opportunities were based in big cities in India might not reflect the real opportunities at Tier-2 and Tier-3 places.

Lacking Information: However, about thirty per cent of the data do not have salary disclosures, and it may undermine the strength of wage-trend analysis.

Ethical Data Use: The postings that were harvested were only those that were publicly made available. Data were handled according to the Theory of Fair Use and anonymised to protect privacy and comply with the guidelines of the platform.

Meeting these challenges in the future will be possible by using API integrations, bias-reduction measures, and regular data quality audits.

## X. FUTURE WORK

The development of the Live Job Market Trend Analyzer will focus on the following:

Integrating more APIs from LinkedIn, Naukri, and Glass- door to provide better coverage across different platforms.

We propose improved accuracy in forecasting models using Prophet and LSTM-based trending.

Deploying a Flask web interface that includes the Power BI dashboard, making it publicly available.

Building a mobile companion application that offers personalized insights and daily job trend alerts.

Working with academic placement cells to develop automated skill-gap reports that link academic coursework to market demand.

These changes will improve the system's usability, accuracy, and social impact, making it an integrated labour market intelligence platform.

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