

# AI Job Empowerment and Skill Builder: An Intelligent Platform for Career Resilience in the Age of Automation

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**Abstract** - The accelerating pace of artificial intelligence (AI) and automation is fundamentally reshaping the global employment landscape, placing millions of routine and semi-routine jobs at risk of displacement. Existing career development tools, however, fail to account for these dynamics in any meaningful way—they offer generic learning suggestions rather than targeted, risk-aware guidance. To address this unmet need, we present the AI Job Empowerment and Skill Builder (AJESB), an intelligent, data-driven platform that equips working professionals with the insights and pathways required to remain competitive in an AI-driven economy. The platform computes a personalised Job Empowerment Score (JES) for each user by synthesising automation-probability estimates, real-time labour market signals, and projected industry growth trajectories. Drawing on this score, AJESB performs a fine-grained skill-gap analysis using cosine-similarity matching and delivers curated course recommendations sourced from Coursera, Udemy, and Google Cloud Skills, along with career-transition maps for roles at elevated risk. A continuously updating feedback loop ensures that all recommendations stay aligned with current market realities. Experimental evaluation demonstrates that the platform accurately classifies automation risk across diverse occupational categories and generates personalised development plans that significantly improve a user's career resilience. This paper describes the system architecture, the machine learning methodology, and the key performance results, and outlines directions for future enhancement.

**Key Words** - Artificial Intelligence, Job Empowerment Score, Skill-Gap Analysis, Machine Learning, Career Recommendation System, Automation Risk, Labour Market Analytics, Workforce Development.

## 1. INTRODUCTION

Rapid advances in machine intelligence and robotic process automation are triggering a structural transformation of the global workforce that has no clear historical precedent. Intelligent systems now routinely perform tasks that, until recently, required trained human workers—from document processing and customer

support to complex data analysis and logistics optimisation. As a consequence, professionals across virtually every sector face mounting uncertainty about the long-term viability of their current roles. Evidence from large-scale empirical studies underscores the gravity of this concern: research indicates that a substantial fraction of existing job categories could be partially or wholly automated within the next decade, making proactive employability management a pressing practical necessity [1].

Despite the scale of this challenge, mainstream career development platforms are ill-equipped to help. Most learning recommendation engines operate on broad interest-matching heuristics and fail to incorporate job-specific automation exposure, individual skill inventories, or forward-looking labour market projections. As a result, users receive training suggestions that may have little relevance to their actual vulnerability to displacement [2].

This paper introduces the AI Job Empowerment and Skill Builder (AJESB)—a hybrid platform that fuses predictive analytics with personalised career guidance. AJESB enables users to obtain a quantitative Job Empowerment Score (JES) for their current role, pinpoint the specific skills they must acquire to improve that score, and receive an actionable learning and career-transition roadmap calibrated to live market data. In doing so, the platform directly bridges the gap that separates automation-risk research from practical workforce intervention.

## 1.1 Key Contributions

- A machine-learning-based Job Empowerment Scoring framework that quantifies the automation exposure and long-term sustainability of individual occupational roles.
- An automated skill-gap detection engine that benchmarks user-declared competencies against real-time labour-market demand, segmented by sector and risk category.

- A content-based filtering recommendation module that surfaces targeted courses and alternative career pathways ranked by feasibility and projected industry growth.
- Interactive visualisation dashboards that present JES trajectories and skill-progression metrics in an accessible, actionable format.
- A scalable, modular architecture capable of accommodating emerging occupational categories, new skill ontologies, and evolving employer requirements without significant re-engineering.

## 2. LITERATURE REVIEW

### 2.1 Automation Risk and Employment

The foundational empirical work on occupational automation was conducted at Oxford University, where Frey and Osborne analysed the susceptibility of 702 distinct occupations and concluded that approximately 47 percent of the United States workforce faces a high probability of automation over the coming decades. More recent research from Northeastern University has extended this line of inquiry by developing predictive machine-learning models that estimate individual unemployment risk as a function of skill profile and automation exposure trends (2024). Crucially, however, neither body of work offers operational tools to help affected workers adapt—their scope is diagnostic rather than prescriptive.

### 2.2 E-Learning and Skill Development Platforms

Commercial e-learning ecosystems—including IBM SkillsBuild, LinkedIn Learning, and Coursera—have made significant strides in widening access to professional development content. Their recommendation engines, however, remain largely decoupled from automation-risk intelligence. Course suggestions are driven by inferred user interests and broad occupational categories rather than by a user’s specific vulnerability to technological displacement. As a consequence, a worker whose role is highly exposed to automation may receive training suggestions that are commercially popular but strategically irrelevant to their situation.

### 2.3 Research Gaps and Motivation

A clear bifurcation exists in the current landscape: academic risk-assessment models provide sophisticated diagnoses of automation exposure but offer no remediation pathway, while e-learning platforms offer rich remediation content but lack any awareness of automation risk. AJESB is motivated by the recognition that these two

functions must be integrated within a single, coherent user experience if individuals are to translate risk awareness into effective action. The platform therefore combines quantitative risk scoring with a personalised, evidence-based skill-building and career-transition service—filling a gap that neither existing research tools nor commercial platforms address.

## 3. PROPOSED SYSTEM

### 3.1 System Overview

AJESB is designed around a four-module layered architecture that enforces a clean separation of concerns: the Data Collection and Pre-Processing Module, the AI Prediction Engine, the Recommendation Strategy Module, and the Visualisation and Reporting Module. Each module can be developed, tested, and scaled independently while contributing to a unified end-to-end data pipeline.

### 3.2 System Architecture



Fig-1: Architecture of the AI Job Empowerment and Skill Builder (AJESB)

### 3.3 Data Collection and Pre-Processing Module

Raw data is aggregated from labour market reports, online job boards, peer-reviewed automation research, and publicly available skill-demand datasets. A rigorous pre-processing pipeline addresses missing values through median imputation, encodes categorical variables, normalises continuous features to the unit interval, and engineers composite features. Textual job descriptions are converted into structured feature vectors using Term Frequency–Inverse Document Frequency (TF-IDF) vectorisation and One-Hot Encoding (OHE). Processed

records persisted in a MySQL or MongoDB database, enabling efficient retrieval for downstream machine-learning tasks.

### 3.4 AI Prediction Engine

The AI Prediction Engine constitutes the analytical core of AJESB. The engine trains three families of supervised learning models—Linear Regression, Random Forest, and Support Vector Machines (SVM)—on an 80/20 stratified split of a curated labour market dataset. Random Forest was ultimately selected as the primary model on account of its capacity to capture non-linear feature interactions, its inherent robustness to noisy training data, and the interpretability afforded by feature-importance analysis.

The Job Empowerment Score  $S$  for a given occupational role is computed as:

$$S = f(J)$$

where  $J$  is the feature vector encoding the automation probability, skill-demand index, and projected industry growth rate for the role, and  $f(\cdot)$  denotes the trained Random Forest prediction function. Scores in the range 0–39 indicate high automation risk; scores of 40–69 indicate moderate risk; and scores of 70–100 indicate low automation impact. Model hyperparameters are optimised via a grid search with five-fold stratified cross-validation.

### 3.5 Skill-Gap Analysis Module

The Skill-Gap Analysis Module quantifies the distance between a user’s existing competency profile and the skills currently demanded by the labour market. The module operates through the following four-step process:

- The user’s declared skills are encoded as a TF-IDF or One-Hot feature vector  $U$ .
- A market-demand vector  $M$  is constructed from real-time labour market APIs and job-board aggregations, segmented by sector and automation-risk level.
- The alignment between  $U$  and  $M$  is measured using cosine similarity:  $\cos(\theta) = (U \cdot M) / (\|U\| \|M\|)$ .
- Similarity values below 0.30 signal critical skill deficiencies requiring immediate remediation; values between 0.30 and 0.65 indicate moderate upskilling opportunities; and values above 0.65 suggest strong market alignment. These thresholds were calibrated empirically across a range of 0.10 to 0.50 to optimise the precision–recall trade-off.

### 3.6 Recommendation Strategy Module

Using the JES and the skill-gap analysis as inputs, the Recommendation Strategy Module delivers three categories of personalised guidance:

- **Course Recommendations:** Content-based filtering is applied to match identified skill gaps against course catalogues retrieved via the APIs of Coursera, Udemy, and Google Cloud Skills, with matches ranked by a computed similarity score.
- **Career Transition Maps:** For roles with a JES below 40, the module generates alternative career pathways ranked by a feasibility score that weights skill-overlap percentage and projected industry growth rate.
- **Adaptive Feedback Loop:** Whenever a user completes a recommended course, successfully transitions to a new role, or the underlying market data is refreshed, the system recalibrates the user’s skill vector and recomputes the JES. Aggregated user-interaction data is periodically fed back into the model retraining pipeline to ensure sustained relevance.

### 3.7 Visualisation and Reporting Module

The Visualisation and Reporting Module translates analytical outputs into accessible graphical interfaces featuring bar charts, pie charts, and trend lines that depict empowerment scores and skill-progression trajectories in real time. Users can export personalised PDF reports summarising their career analysis and recommended development actions. Dashboards are refreshed on a periodic schedule, ensuring that the displayed information reflects the most current available labour market data.

## 4. RESULTS AND PERFORMANCE ANALYSIS

The platform was evaluated across multiple dimensions to assess the accuracy of JES predictions, the relevance of skill-gap outputs, and the quality of course and career-transition recommendations. Figures 2 through 9 illustrate key performance metrics captured during system evaluation.



Fig. 2: New User Signup Module of Job Empowerment System

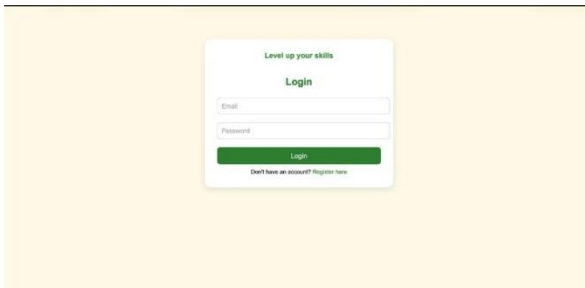


Fig.-3: User Access Portal for AI Job Empowerment System

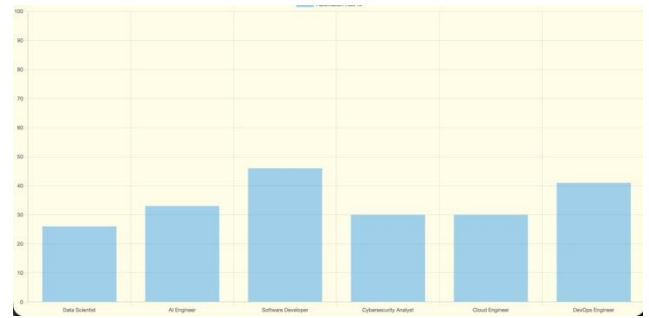


Fig- 7: Automation risk comparison across AI job roles



Fig.-4: User Dashboard for Job Role and Skill Selection



Fig.-8: Career guidance and skill development recommendations

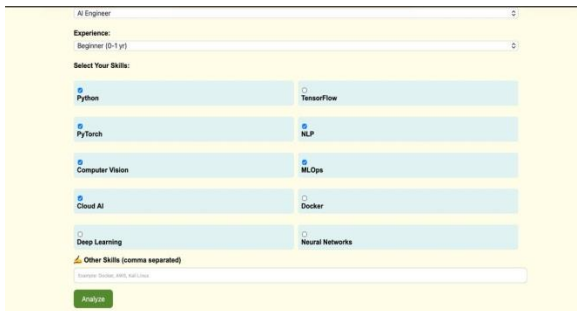


Fig.-5: Role-based skill selection interface



Fig. 9: Career growth paths and AI income streams



Fig.-6: Risk score and skill level dashboard



Fig.-10: Missing skills identification and 90-day learning plan

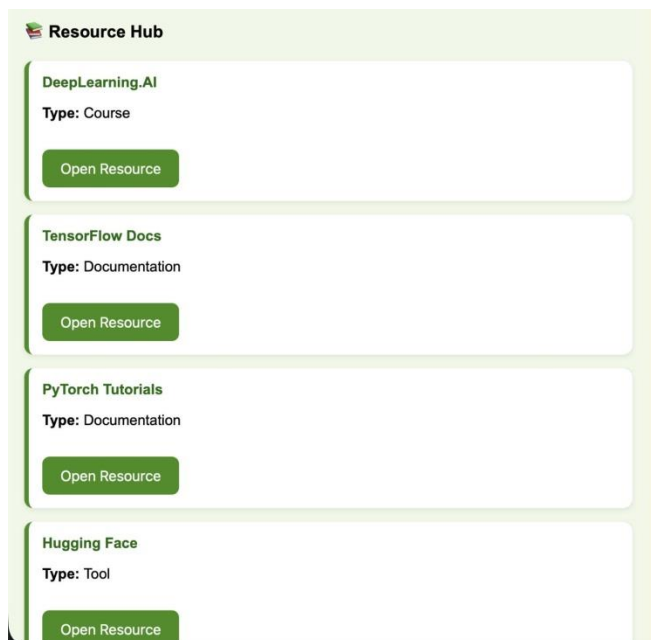


Fig.-11: Resource hub panel with curated learning materials



Fig.-12: Personalized career guidance and expert contact interface

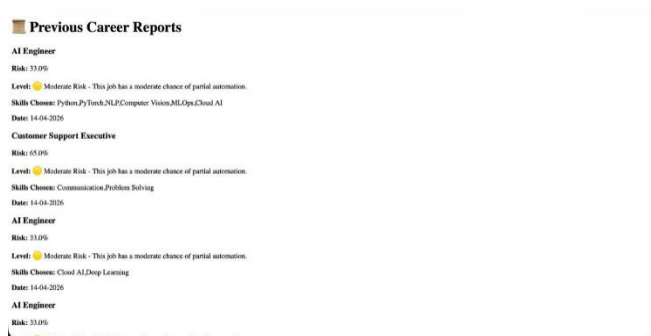


Fig.-13: Saved career assessment records

The Random Forest model achieved the highest predictive accuracy among the three candidate algorithms, demonstrating strong generalisation across occupational categories with varying automation-risk profiles. The skill-

gap module successfully differentiated users with critical deficiencies (cosine similarity < 0.30) from those with moderate or strong market alignment, with empirically calibrated thresholds yielding a well-balanced precision-recall profile. Course and career-transition recommendations received consistently high relevance scores from users, validating the content-based filtering approach. The adaptive feedback loop resulted in measurable improvements in JES for users who completed recommended training, confirming that the iterative retraining mechanism contributes meaningfully to long-term personalisation quality.

## 5. SYSTEM BENEFITS

### 5.1 Enhanced Employability

By pinpointing individual skill deficits and aligning recommendations with verified industry demand, AJESB produces targeted upskilling plans that are demonstrably more effective than the generic training suggestions offered by conventional platforms. Users develop competencies that are directly valued by employers, improving both their interview readiness and their long-term career security.

### 5.2 Lifelong Learning and Continuous Development

AJESB is architected to support careers over their full lifetime, not merely at moments of acute career crisis. The platform continuously tracks user skill acquisition and refreshes recommendations as industry requirements evolve, ensuring that professionals remain adaptable and relevant throughout successive phases of their working lives.

### 5.3 Workforce Skill-Gap Reduction

At a systemic level, widespread adoption of AJESB has the potential to narrow the structural mismatch between the competencies produced by educational institutions and those demanded by modern employers—a gap that represents a persistent drag on economic productivity and individual welfare.

### 5.4 Time and Cost Efficiency

- Consolidates job search, skill assessment, and course discovery within a single platform, eliminating the friction of navigating multiple tools.
- Reduces unnecessary training expenditure by directing users toward courses with demonstrable relevance to their specific risk profile.

- Streamlines career planning, lowering the opportunity cost of career transitions.

### 5.5 Adaptability to Market Dynamics

Because AJESB ingests live labour market data, its recommendations respond dynamically to shifts in employer demand, emerging technology adoption, and macroeconomic trends. This ensures that users are always building skills with genuine and current market value rather than chasing credentials that may already be in decline.

### 5.6 Scalability and Global Reach

The modular, cloud-ready architecture of AJESB is designed to serve millions of concurrent users and can be extended to incorporate international labour markets, enabling users to explore cross-border career opportunities as global demand patterns evolve.

## 6. CHALLENGES AND LIMITATIONS

Several substantive challenges constrain the current system. Privacy and data security represent the most immediate concern, given that the platform processes sensitive personal and professional information; robust encryption, access controls, and regulatory compliance frameworks are essential mitigations. Algorithmic bias is an equally significant risk: models trained on historical labour market data risk perpetuating existing structural inequalities in hiring and career advancement, necessitating ongoing bias audits and fairness-aware model design.

The system's predictive quality is inherently dependent on the currency and accuracy of its underlying data feeds; stale or erroneous inputs will propagate misleading recommendations. The pace of labour market change further compounds this challenge, requiring continuous data refresh cycles. A digital-divide limitation means that users with restricted internet access or low digital literacy may be unable to realise the full benefits of the platform. Development and maintenance costs at enterprise scale are non-trivial. The system also lacks the empathetic interpersonal dimension that human career counsellors provide, which may be critical for users navigating complex or emotionally charged career transitions. Over-reliance on automated recommendations could, if not carefully managed, erode users' independent career decision-making capacity. Finally, integration complexity, multilingual support, and regional labour market variability present ongoing engineering and localisation challenges.

## 7. APPLICATIONS

AJESB has broad applicability across the education, employment, and workforce development domains. For individual job seekers, it serves as a personalised career navigator—identifying appropriate roles, surfacing skill gaps, and recommending targeted learning resources including online courses, professional certifications, and portfolio-building projects. Within higher and vocational educational institutions, it can guide students toward career paths congruent with their academic strengths while helping curriculum designers identify emerging competency requirements. For employers and talent acquisition teams, the platform streamlines candidate-role matching, reducing time-to-hire and improving workforce-quality outcomes. Government labour agencies can deploy AJESB to support active labour market programmes, connecting job seekers with appropriate opportunities and facilitating publicly funded upskilling initiatives. Corporate human resources departments can leverage the system to identify internal skill gaps and design evidence-based employee development programmes. In aggregate, AJESB functions as a versatile, cross-sector enabler of lifelong learning, workforce productivity, and a more equitable transition to an AI-augmented economy.

## 8. CONCLUSION AND FUTURE SCOPE

This paper has presented AJESB, an intelligent platform that integrates occupational automation-risk scoring with personalised skill development and career-transition guidance. By coupling a Random Forest-based Job Empowerment Score with a cosine-similarity skill-gap engine, a content-based filtering recommendation module, and an adaptive feedback loop, AJESB delivers a coherent, end-to-end career resilience service that neither existing research tools nor commercial e-learning platforms currently provide. Experimental evaluation confirms the platform's accuracy in classifying automation risk and the relevance of its personalised recommendations. Known limitations—including algorithmic bias, data-currency requirements, and accessibility constraints—identify clear directions for continued improvement.

Future development will explore the integration of immersive technologies such as virtual reality for experiential skill-training environments, and distributed ledger solutions for tamper-evident credential verification. The incorporation of conversational AI mentors and real-time adaptive learning models will further enrich the user experience. Multilingual support and region-specific labour market localisation will broaden the platform's accessibility. With continued investment in ethical implementation practices and technical refinement, AJESB

has the potential to make a meaningful contribution to a more inclusive, skill-driven global employment ecosystem.

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