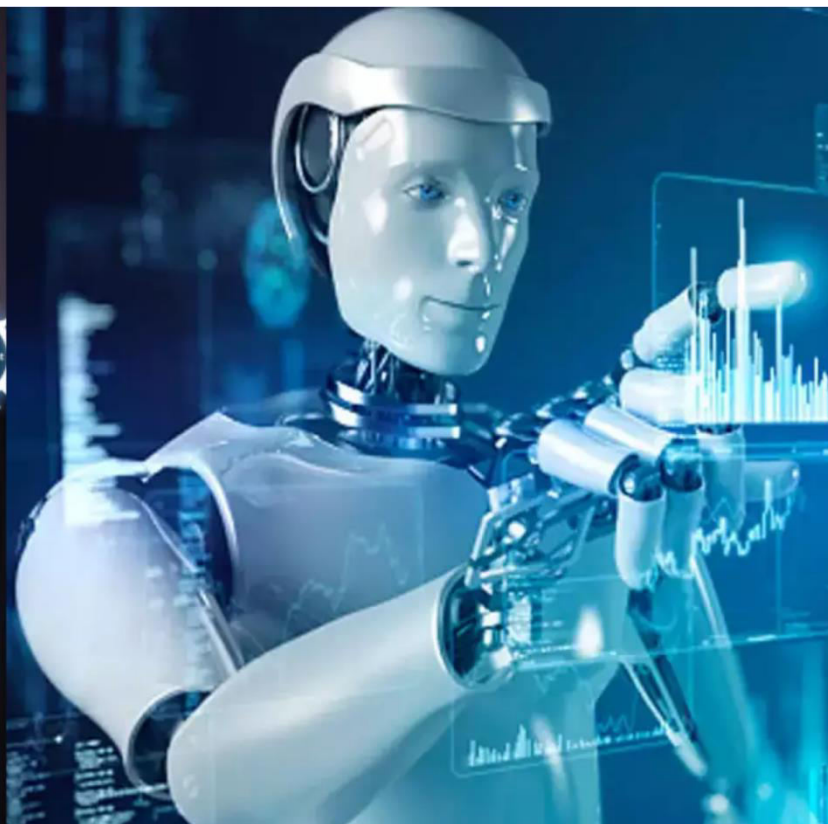




International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 11, November 2025

Designing an Intelligent Career Guidance Ecosystem: Integrating Resume Parsing, Personality Analytics, and Adaptive Learning Pathways

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ABSTRACT: The contemporary job market is undergoing unprecedented transformation, driven by rapid technological advancements, globalization, automation, and the increasing demand for specialized skill sets. This dynamic landscape creates both opportunities and challenges for students, job seekers, and professionals, who often experience decision paralysis when navigating multiple career pathways. Traditional career guidance methods—such as standardized aptitude tests, manual counseling, or generic career portals—typically fail to deliver truly personalized recommendations, as they rarely consider the holistic profile of an individual. A career choice is not merely a function of academic achievements or professional experiences; it is also a synthesis of cognitive abilities, technical competencies, personality traits, and long-term aspirations.

This paper proposes the design and architecture of an AI-powered career guidance system engineered to bridge these critical gaps. The system is designed as a modular framework comprising multiple intelligent components. First, it employs Natural Language Processing (NLP) techniques for automated resume parsing, extracting structured data such as skills, qualifications, certifications, and work experiences from unstructured text. This enables the creation of a comprehensive candidate profile with minimal manual input. Second, the system incorporates a hybrid MBTI classification module, combining rule-based approaches with machine learning classifiers, to assess intrinsic personality traits that strongly influence career satisfaction and performance.

At the core of the recommendation mechanism lies a hybrid career recommender engine, which integrates semantic search models with a knowledge graph-driven career database. Semantic search allows for contextual matching between user profiles and job roles, while the knowledge graph provides structured relationships among careers, required skills, industries, and learning pathways. An advanced skill gap analysis module identifies discrepancies between a user's current competencies and those demanded by target professions. Based on this analysis, the system dynamically generates a personalized learning roadmap, suggesting courses, certifications, and skill-development activities tailored to the individual's profile and career aspirations.

To enhance usability and accessibility, the system is deployed through an interactive AI chatbot interface, enabling real-time, conversational guidance.

I. INTRODUCTION

The transition from education to employment and subsequent career progression are among the most critical and challenging phases in an individual's life. This journey is influenced not only by academic qualifications but also by the alignment of personal interests, intrinsic motivations, and evolving labor market requirements. The proliferation of new job roles, especially in technology-driven sectors such as artificial intelligence, data science, cybersecurity, and renewable energy, has further complicated this process. With the half-life of technical skills shrinking rapidly, the constant need for **reskilling and upskilling** has transformed career planning into a complex, dynamic, and continuous activity rather than a one-time decision.

Students and early-career professionals frequently choose their career paths based on superficial trends, parental influence, or peer pressure rather than an informed assessment of their abilities and aspirations. This often leads to dissatisfaction, career stagnation, or frequent job-hopping. On the other hand, mid-career professionals seeking transitions or new opportunities often struggle with identifying their **transferable skills**, mapping them to emerging roles, and understanding the additional competencies required to remain competitive. As a result, the absence of structured, data-driven guidance creates uncertainty, underemployment, and, in some cases, career misalignment.

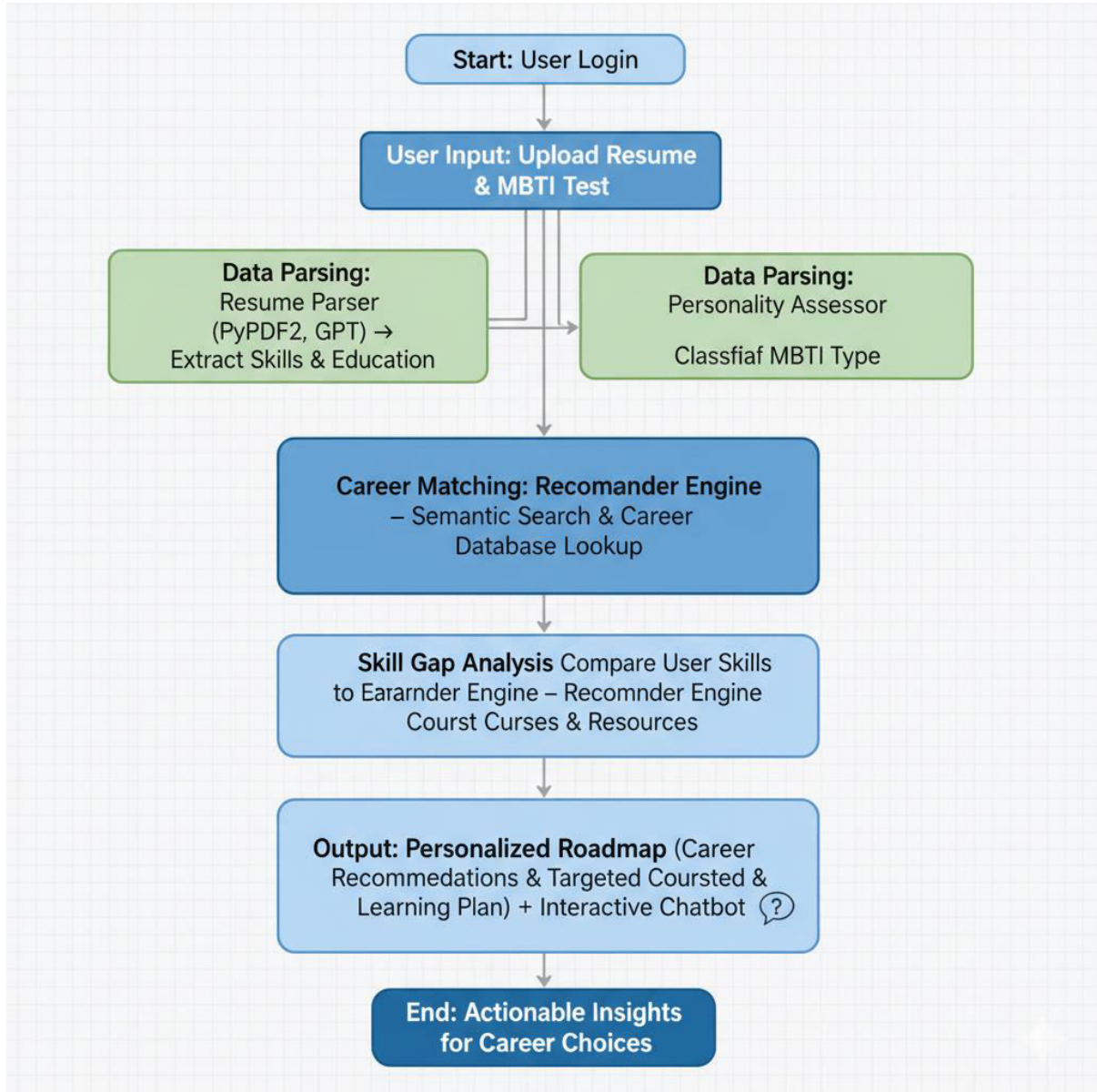
Existing career guidance solutions, while helpful in isolation, are inherently **fragmented and narrow in scope**. Static online quizzes provide oversimplified personality insights, job boards merely list opportunities without context, and one-off counseling sessions cannot adapt to evolving user profiles or market conditions. Moreover, these systems often operate in silos—one platform assesses personality, another provides job listings, and yet another suggests courses—making it difficult for users to piece together a coherent and actionable career development strategy. This siloed approach fails to integrate the **multi-dimensional aspects of a user's profile**, including educational background, hard and soft skills, personality traits, career aspirations, and ongoing progress.

To address these challenges, there is a pressing need for a **unified, intelligent, and adaptive career guidance system** capable of synthesizing diverse user data and aligning it with labor market intelligence. This paper details the design and architecture of such a holistic **AI-based career guidance framework**. The proposed system is engineered to process both **quantitative data** (structured information from resumes, academic records, and skill inventories) and **qualitative data** (psychometric assessments such as personality tests, e.g., MBTI or Big Five). By combining these inputs, the system generates a **tailored career roadmap** that includes recommended job roles, growth opportunities, and targeted learning interventions.

Unlike conventional approaches, the proposed system integrates multiple intelligent modules:

- **Natural Language Processing (NLP)** for automated parsing of resumes and extraction of structured candidate data.
- **Machine learning and rule-based personality classifiers** to derive psychological insights that influence career preferences and workplace behavior.
- **A hybrid recommendation engine** that combines semantic search with knowledge graph lookups, enabling context-aware career recommendations.
- **Skill gap analysis** to identify gaps between current and required competencies for target roles.
- **Dynamic learning path generation**, recommending courses, certifications, or microlearning content aligned with individual needs.

The system culminates in an **interactive conversational AI interface**, ensuring accessibility and continuous engagement. This not only provides career recommendations but also supports iterative refinement as users progress through their career journey. In doing so, the system offers a **360-degree view of career possibilities**, making personalized career planning **scalable, adaptive, and data-driven**.



II. SYSTEM ARCHITECTURE & METHODOLOGY

The proposed system follows a sequential pipeline, as outlined in the provided flowchart, with each module performing a specific function and feeding its output to the next.

2.1. Module 1: User Authentication and Data Input

- **Process:** The user logs into the system, creating a personalized profile.
- **Inputs:** The system requires two primary inputs:
 1. **Resume/CV Upload:** Accepts documents in common formats (PDF, DOCX). This provides structured and unstructured data on skills, work experience, education, certifications, and projects.
 2. **MBTI Personality Test:** A digital adaptation of the standard 93-question forced-choice Myers-Briggs Type Indicator assessment. This provides insights into the user's psychological preferences regarding energy direction (Extraversion/Introversion), information processing (Sensing/Intuition), decision-making (Thinking/Feeling), and lifestyle structure (Judging/Perceiving).

2.2. Module 2: Data Parsing and Feature Extraction

2.2.1. Resume Parser (NLP Engine)

- **Technology Stack:** PyPDF2/Tika for text extraction from PDFs, followed by advanced NLP libraries like SpaCy or NLTK for tokenization, named entity recognition (NER), and part-of-speech (POS) tagging. A Large Language Model (LLM) like GPT-3.5/4 can be employed for superior context understanding and extraction from complex, non-standard resume formats.
- **Function:** This module deconstructs the resume to extract key entities:
 - **Skills:** Identifies technical skills (e.g., Python, SQL, CAD), soft skills (e.g., Leadership, Communication), and tools.
 - **Education:** Extracts degrees, institutions, graduation years, and fields of study.
 - **Experience:** Parses job titles, companies, tenure, and bullet points describing responsibilities and achievements.
 - **Output:** A structured JSON object categorizing all extracted information, which is stored in the user profile.

2.2.2. Personality Assessor (MBTI Classifier)

- **Methodology:** The user's responses to the questionnaire are scored based on the standard MBTI scoring key. Each response contributes to one of four dichotomies.
- **Advanced Implementation:** Beyond a simple questionnaire, machine learning can be used to refine the model. A dataset of question-answer pairs mapped to MBTI types can train a classifier (e.g., Random Forest, SVM) to predict type, potentially identifying patterns or inconsistencies. Sentiment analysis and NLP on open-ended questions could provide additional validation.
- **Output:** A four-letter MBTI code (e.g., INTP, ESFJ) and a confidence score.

2.3. Module 3: The AI-Powered Recommender Engine (Core Intelligence)

This is the core analytical module that synthesizes data from all sources.

- **Knowledge Base:** A comprehensive and dynamic database of career roles. Each role is enriched with metadata including:
 - Required and recommended skills (hard and soft).
 - Typical educational backgrounds.
 - Personality traits that are commonly associated with success and satisfaction in that role (e.g., an Software Developer might often correlate with INTP/ISTP types, while a Marketing Manager might align with ENFJ/ENTP).
 - Industry trends, salary ranges, and future growth outlook.
 - Related career paths for lateral movement.
- **Matching Algorithm:** A hybrid approach is most effective:
 1. **Content-Based Filtering (Skill & Education Matching):** Matches the user's extracted skills and education against the requirements of careers in the database using cosine similarity or other NLP similarity measures.
 2. **Collaborative Filtering (Personality & Pattern Matching):** Leverages the MBTI type and data from other users. "Users with similar skills and personality types have followed these paths..." This requires a large dataset of user profiles and outcomes.
 3. **Semantic Search:** Allows the engine to understand the context and relation between terms. For example, it understands that "NLP" is related to "Natural Language Processing" and "Machine Learning," and that "project management" is a skill adjacent to "Agile" and "Scrum Master."
- **Output:** A ranked list of recommended career paths, each with a compatibility score explaining the match based on skills, education, and personality fit.

2.4. Module 4: Skill Gap Analysis & Learning Path Generator

- **Process:** For each top career recommendation, the system performs a differential analysis.
 - It compares the user's current skill set (from the resume parser) with the required skill set for the target job.
 - It identifies missing "must-have" skills and "good-to-have" skills.

Volume 14, Issue 11, November 2025**|DOI: 10.15680/IJIRSET.2025.1411072|**

- **Resource Integration:** The system is integrated with APIs from major online learning platforms (Coursera, Udemy, edX, LinkedIn Learning) and free resources (YouTube tutorials, blogs, documentation).
- **Personalized Roadmap Generation:** For each skill gap, the system curates a sequence of learning resources. It creates a structured, timed learning plan, suggesting beginner to advanced courses, practical projects, and readings. The plan is adaptive; as a user completes courses (manually marked or verified via API), the roadmap updates.

III. TECHNOLOGICAL IMPLEMENTATION STACK

- **Backend:** Python (Django/Flask/FastAPI) for business logic and API development.
- **NLP Libraries:** SpaCy, NLTK, Transformers (Hugging Face) for resume parsing and semantic search.
- **ML Libraries:** Scikit-learn, TensorFlow/PyTorch for the MBTI classifier and recommender algorithms.
- **Database:** PostgreSQL or MongoDB for storing user profiles, career database, and learning resources.
- **Frontend:** React.js or Vue.js for building a dynamic and responsive dashboard.
- **Chatbot:** Rasa framework or a custom implementation using OpenAI's API.
- **Deployment:** Docker containers deployed on a cloud platform (AWS, Azure, GCP) for scalability.

IV. CHALLENGES AND CONSIDERATIONS

- **Data Privacy & Security:** Handling sensitive user data (resumes, personality) requires strict encryption, anonymization practices, and compliance with GDPR/CCPA.
- **Bias in AI:** The training data for the resume parser and recommender engine must be meticulously curated to avoid perpetuating gender, racial, or socioeconomic biases in career recommendations.
- **MBTI Validity:** While popular, the MBTI's scientific validity is debated in psychology. The system should present results as suggestive insights rather than absolute truths and could be extended to incorporate other, more robust personality models (e.g., Big Five OCEAN).
- **Dynamic Market Data:** The career database must be continuously updated with real-time job market data from sources like LinkedIn and Indeed APIs to reflect evolving skill demands.

V. CONCLUSION AND FUTURE WORK

This paper presents a robust architecture for an AI-driven career guidance system that moves beyond generic advice to offer truly personalized, actionable insights. By integrating resume parsing, personality assessment, and intelligent recommendation algorithms, the system provides a holistic view of a user's career options. The interactive chatbot and dynamic learning roadmap ensure continuous engagement and support throughout the user's career development journey.

Future iterations of this system could include:

- **Integration with professional networks** (e.g., LinkedIn) to automatically update user skills and connect them with mentors in their desired field.
- **Advanced predictive analytics** to forecast future career trends and emerging roles.
- **A mentorship matching module** connecting users with experienced professionals based on career goals and personality compatibility.
- **Gamification** of the learning pathway to increase user motivation and completion rates.

This system holds significant potential for educational institutions, universities, and corporations to support the career development of their students and employees, ultimately leading to more informed, satisfied, and successful workforce.

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