International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

# Career Assessment and Recommendation System

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*Abstract*— Selecting the right career path is one of the toughest choices for students and job seekers. Many people find it hard to identify careers that match their skills, interests, and education. Traditional career guidance often feels too general and lacks a personal touch. To tackle this problem, this paper suggests an AI- Based Career Assessment and Recommendation System that offers customized career suggestions using data- driven methods.

This system gathers user information through resume submissions, interest questionnaires, aptitude tests, and evaluations of technical skills. It processes this data with advanced algorithms and machine learning techniques to pinpoint the user's strengths, preferences, and skill levels. From this analysis, it recommends suitable career paths along with the relevant courses and educational resources needed to achieve those career goals.

Keywords: Career Recommendation, Career Assessment, Artificial Intelligence, Machine Learning, Personalized Guidance, Skill Analysis.

## Introduction

Choosing the right career can be a long and confusing process for students and job seekers. As technology advances quickly and new job roles emerge, individuals must sort through a lot of information before deciding. Identifying suitable career fields, understanding the necessary skills, comparing different job roles, and finding relevant courses require significant time and effort. Many students struggle to connect their studies, personal interests, and technical skills withreal-world job opportunities.

Selecting a career involves more than just picking a job title. It means combining personal interests, skills, personality traits, and the needs of different industries. Research in career development shows that not knowing one's interests and strengths can lead to poor career choices, dissatisfaction, and underperformance. Factors like peer pressure, parental expectations, social influences, and market trends greatly influence career decisions. However, without clear guidance, students may choose paths that do not align with their true abilities or long-term goals.

Recent studies on career recommendation systems focus on using Artificial Intelligence (AI), data mining, and machine learning to analyze user profiles and provide data-driven suggestions. Current systems often match technical skills with job requirements or recommend courses based on academic records. Some methods rely on resume analysis, text mining, or job profile matching to generate recommendations. Although these systems help with career guidance, many focus on skill matching and overlook important aspects like personal interests, skill levels, and overall personality assessments.

Another problem with earlier models is that they fail to link educational performance, technical evaluations, and psychological factors. In many cases, systems suggest careers based solely on qualifications or keyword matches, without confirming if the recommended path fits the individual's interests and skill levels. Additionally, the processes for validating suggested learning paths are often limited.

To address these issues, this study introduces an AI-Based Career Assessment and Recommendation System that integrates various aspects of career evaluation. The system combines resume analysis, interest surveys, aptitude tests, and technical skill evaluations to form a complete user profile. By using data analysis and machine learning, the system identifies patterns between user traits and suitable career paths. Unlike

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

traditional models, this new approach considers both technical skills and personal interests for more relevant and tailored recommendations.

The main goal of this research is to create a smart, scalable, and user-friendly system that serves as a virtual career advisor. The system not only proposes career paths but also recommends appropriate courses and resources for skill development, helping users achieve their professional goals. By linking education with industry needs, this proposed system aims to clarify career paths, enhance employability, and support students and job seekers in making informed choices.

Key Contributions:

The development of the proposed AI-Based Career Assessment and Recommendation System offers several significant contributions to the field of intelligent career guidance. The system is built as a modular and scalable platform that combines various evaluation components. These include resume analysis, interest surveys, aptitude assessment, and technical skill evaluation, which together provide a thorough understanding of user profiles. A major contribution of this work is the introduction of a hybrid recommendation framework.

This framework combines rule-based filtering with machine learning prediction techniques. The rule-based layer creates structured relationships between academic backgrounds and career paths. Meanwhile, the prediction layer analyzes user data patterns to produce tailored recommendations. This hybrid approach improves both the system's accuracy and its flexibility. Another innovative aspect of the proposed system is its multi-dimensional profiling strategy.

Unlike traditional systems that focus solely on academic performance or keyword matching, this model examines interests, aptitude levels, technical skills, and learning styles together. This ensures that suggested careers are aligned with skills and interests, minimizing the chance of career mismatches. Additionally, the system features an explainable recommendation mechanism.

Users receive clear explanations for the suggested career paths. The recommendations include a breakdown of matched skills, interest compatibility, and areas for improvement. This transparency builds user trust and aids in making informed decisions. The platform also offers structured course and certification recommendations linked to each career suggestion. This changes the system from a basic recommendation engine into a complete career planning assistant, creating a connection between education and industry needs.

The effectiveness of the system is measured using performance metrics like recommendation accuracy, user satisfaction feedback, and relevance scoring. Experimental results show that combining technical skills, aptitude assessment, and interest analysis significantly enhances the quality of career recommendations compared to models based on a single factor. Overall, the proposed system serves as a scalable, data-driven, and user-focused solution that tackles key challenges in career guidance, especially the need for personalized support and structured decision-making.

The rest of this paper is organized as follows. Section II presents the Literature Review related to AI-driven career recommendation systems and educational data mining approaches, Section III describes the Proposed System Architecture and overall framework of the Career Assessment and Recommendation System, Section IV explains the System Implementation, including data collection, model integration, and technology stack, Section V details the Experimental Setup and evaluation methodology, Section VI presents the Results and Analysis of the system's performance, Section VII discusses the findings and practical implications of the proposed model, Section VIII outlines the Future Scope and possible enhancements, Finally, Section IX concludes the paper with a summary of contributions and outcomes.

**Literature Survey:**

In recent years, Artificial Intelligence recommendation systems have become common in education and recruitment. These systems help students and job seekers make informed career choices. Various studies have sought to bridge the gap between academic learning and industry needs.

[1] Title: A Hierarchical and Multi-Tiered Personalized Career Recommender System Tailored to Individual Aptitudes

Authors: M. Noushad Rahim, K.P. Mohamed Basheer Published: Indian Journal of Science and Technology, 2025

Problem Statement:

In India, there are not enough career counsellors for the number of students. Current career recommendation systems focus on specific fields and face issues like cold starts and a lack of data. This paper suggests an automated machine learning solution.

Methodology:

User Profile Generation: Kerala Differential Aptitude Test (KDAT) includes 180 questions across 6 areas: NA, AR, VR, MR, SR, VA, Scores were standardized using Z-score normalization.

Career Profile Generation: Extracted 612 real-world careers from the O*NET database, Mapped O*NET ability parameters to DAT batteries, Applied K-Means Clustering resulting in 8 top-level and 49 sub-level clusters.

Data Augmentation: Expanded the original 612 records to 57,109 using Gaussian Noise. This approach helped address the overfitting issue.

Model: A Voting Classifier combines ANN, SVM, KNN, Random Forest, Decision Tree, and Gaussian Naive Bayes.

System Architecture (Two Modules):

Diverse Recommender Module identifies the top 3 career separates Refined Recommendation Module recommendations into Tier 1, Tier 2, and Tier 3. The total output includes 9 sets of diverse career recommendations.

Key Contributions:

Created a unique dataset with 612 real-world careers, Addresses cold start and data sparsity challenges. Provides multi-tiered diverse recommendations instead of just one.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Offers a visualization of career clusters for clarity, Decreases subjectivity in career counselling.

Limitations :

Personality traits and vocational interests have not yet been included, An explainable AI framework can be implemented for greater transparency.

[2] Title: Improving Graduate Outcomes by Identifying Skills Gaps and Recommending Courses Based on Career Interests

Authors: Rahul Soni1, Basem Suleiman1, Sonit Singh

Problem Statement:

There are too many course options in university. Students struggle to choose the right ones. What they study often does not match what companies need.

Methodology:

We collected course data and job data. We cleaned the text and identified skills using AI tools. We grouped similar courses together.

System Architecture:

The system has three parts: a website for students, a database for storage, and an AI model for suggestions. Students upload their resumes, the system finds missing skills, and suggests courses.

Result:

Users were satisfied. The skill detection feature was helpful. The system worked well.

Limitation:

The system only identifies technical skills. It cannot find soft skills and lacks accessibility support.

[3] Title: Unlocking Futures: A Natural Language Driven Career Prediction System for Computer Science and Software Engineering Students

Authors: Sakir Hossain Faruque, Sharun Akter Khushbu, Sharmin Akter from Daffodil International University, Dhaka, Bangladesh

Problem Statement:

CS and Software Engineering students struggle to choose the right career path after finishing their degree. The many job options in the IT field can confuse graduates. A gap between what students learn and what the job market requires can result in poor job performance and dissatisfaction. Most current systems do not use NLP techniques for career prediction, which limits their accuracy and usefulness.

Methodology:

We gathered student data from various universities in Bangladesh using a Google Form survey. The survey collected information about students' skills, interests, preferred career fields, and related activities. About 19% chose software development, 13% chose web development, and 13% chose cybersecurity as their preferred paths.

We manually cleaned the collected data by grouping rarely chosen fields into broader master categories. We removed irrelevant columns, such as semester and course. Then, we applied NLP techniques including stop word removal, lowercasing, label encoding, and text vectorization. We split the dataset so that 80% was used for training and 20% for testing.

System Architecture:

The system follows a step-by-step pipeline:

Data Collection: Google Form survey from students across Bangladesh.

Preprocessing: Manual cleaning, noise removal, NLP processing, vectorization.

Model Training: Several ML and deep learning algorithms trained on processed data.

Prediction Output: The SVM model provides percentage-based career predictions for each student based on their input skills.

We defined six master career categories: AI, Data Science, Development, Security, Software Engineering, and UI/UX.

Key Contributions:

This is the first study to use NLP techniques specifically for career prediction for CS and SWE students in Bangladesh. We tested eight different algorithms: DT, SVM, LR, KNN, NB, CNN, MLP, LSTM, and compared all results. SVM achieved the best accuracy at 88.63% and the highest precision at 91.82%.

The system provides percentage-based career suggestions, making it easy for students to understand their best options. It helps career counsellors and academic advisors guide students more effectively.

Limitations:

The dataset size is small, which impacts model performance.

The system currently focuses only on CS and SWE students.

Future work plans include expanding to other academic departments and increasing dataset size for improved accuracy.

[4] Title: Unlocking Futures: A Natural Language Driven Career Prediction System for CS and SWE Students

Authors: Faruque, Khushbu, Akter, Daffodil International University, Bangladesh

Problem Statement :

The growth of the IT industry has opened up many career options for CS and Software Engineering graduates. Without proper guidance, students often struggle to find the right path for them. A gap exists between what students learn and what the job market truly needs. This can lead to poor career choices, low job performance, and dissatisfaction. Most existing systems rely on traditional methods and do not use NLP, which limits the quality of their predictions.

Methodology:

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

We collected student information from several universities in Bangladesh using a Google Form survey. The questions asked about preferred career fields, important skills, core courses, and career-related activities. Approximately 19% of respondents chose software development, 13% selected web development, and another 13% opted for cybersecurity as their top choices.

We manually cleaned the raw data by grouping less common fields into six main categories: AI, Data Science, Development, Security, Software Engineering, and UI/UX. Inconsistent entries were corrected or removed. We applied NLP techniques including stop word removal, lowercasing, label encoding, and text vectorization. The data was split with 80% for training and 20% for testing, with shuffling to prevent bias.

System Architecture:

The system follows a five-step pipeline:

Step 1: Survey data was collected via Google Forms from universities in Bangladesh

Step 2: Manual and automatic data cleaning along with NLP preprocessing were applied

Step 3: Eight machine learning and deep learning models were trained: DT, SVM, LR, KNN, NB, CNN, MLP, LSTM

Step 4: All models were compared based on accuracy, precision, recall, and F1 score

Step 5: SVM was selected as the final model; it takes student skills as input and provides percentage-based career predictions as output.

Key Contributions:

This is the first study to use NLP techniques specifically for CS and SWE student career prediction. We tested and compared eight different algorithms, providing a detailed performance analysis. SVM achieved the best overall results, making it the selected prediction model.

The system outputs career predictions as percentages, making it easy for students to see their best fit. This is useful for students, academic advisors, and career counsellors. SVM also achieved the highest precision of 91.82% and the highest F1 score of 88.56%.

Limitations:

The dataset is small, which affects how well the model generalizes.

The study is limited to CS and SWE students in Bangladesh.

Future work plans to include more academic departments and expand the dataset to improve accuracy and reduce processing time.

[5]Title: JobRecoGPT: Explainable Job Recommendations using Large Language Models

Authors: The paper was written by Preetam Ghosh and Vaishali Sadaphal. They focused on creating an AI-based job recommendation system using Large Language Models (LLMs).

Problem Statement:

Many job recommendation systems rely on structured resume data. They convert resumes and job descriptions into fixed formats like skill lists or keyword vectors to make recommendations. During this process, important details such as candidate aspirations, soft skills, career goals, and work preferences often get lost.

The authors noted that losing this information impacts the quality and personalization of job recommendations. Thus, the main problem addressed in this paper is:

How can we generate accurate, personalized, and explainable job recommendations directly from unstructured text without losing meaningful information?

Methodology:

To tackle this problem, the authors investigated Large Language Models (LLMs), especially GPT-based models. They experimented with four different approaches:

Content-Based Deterministic Approach: This method uses structured matching techniques. It compares candidate skills with job requirements using predefined scoring rules.

LLM-Guided Approach: The LLM receives structured prompts and evaluation criteria. It recommends jobs and offers explanations based on guided reasoning.

LLM-Unguided Approach: In this approach, the LLM analyses the resume and job descriptions freely and suggests suitable roles based on its understanding.

Hybrid Approach: This combines rule-based filtering with LLM reasoning. First, structured filtering narrows down job options. Then, the LLM provides qualitative explanations and rankings.

The system was tested using synthetic datasets and real-world IT job descriptions. The authors evaluated each approach based on recommendation accuracy and reasoning quality.

System Architecture:

The system architecture has the following main components:

Input Layer – Accepts unstructured resumes and job descriptions.

Preprocessing Layer – Cleans and prepares the textual data.

Recommendation Engine - Deterministic module for skill matching, LLM module for semantic analysis and reasoning

Ranking and Explanation Module – Offers top job suggestions with explanations detailing why the job matches, its advantages, and possible drawbacks.

Output Layer – Displays ranked job recommendations with justification.

The hybrid model combines structured and unstructured analysis to balance scalability and quality.

Key Contributions:

The main contributions of this paper include:

The introduction of LLM-based job recommendations that do not rely entirely on structured data.

A comparison of deterministic, LLM-guided, unguided, and hybrid models.

Evidence that LLM-based approaches can enhance qualitative reasoning in job matching.

The provision of explainable recommendations rather than just similarity scores.

Demonstration that hybrid systems achieve better scalability and a practical balance in implementation.

Limitations:

While the system shows promising results, it has some limitations:

High computational cost due to LLM usage.

Token limits and runtime constraints.

Scalability challenges for large-scale deployment.

A limited evaluation domain, mainly focused on the IT sector.

Lack of integration for aptitude testing, personality analysis, or long-term career planning.

Failure to consider real-time dynamic labour market trends

[6] Title: Career Path Prediction using Resume and Skill Analysis

Authors: A group of researchers from a European university and an industry research team conducted this work.

Problem statement:

Choosing the next step in a career can be challenging. Many current career recommendation systems attempt to address this by analysing job titles or leveraging large professional networking databases. However, these systems often rely on extensive private datasets and mostly focus on role names rather than understanding what a person actually did in their previous jobs.

Resumes contain valuable information such as:

- Responsibilities handled

- Tools and technologies used

- Nature of projects worked on

- Practical exposure

Yet, most traditional systems overlook this detailed textual information. As a result, career predictions often lack depth and personalization. The researchers aimed to answer a simple but significant question:

Can we predict someone's next career role by closely analysing resume descriptions and accumulated skills, even if the dataset size is not very large?

Methodology:

To explore this idea, the authors tested three different strategies.

Skill-Oriented Method: In the first method, the system focused mainly on skills gained from past job roles. Each occupation links to a set of required skills. By comparing skills already acquired by the candidate with skills needed for potential future roles the system calculates a similarity score. The main idea is that career growth occurs when skill sets gradually evolve and expand. This method is organized and straightforward to implement, but it may lack contextual understanding.

Resume Text-Based Method: In the second method,

instead of concentrating solely on skills, the researchers analysed the actual text from resumes.

For instance:

- Descriptions of daily tasks

- Type of environment worked in

- Domain exposure

By translating these textual descriptions into numerical representations (embeddings), the system seeks to grasp deeper meanings and professional patterns. This method

captures:

- Career direction

- Domain consistency

- Functional role similarity

It offers a broader understanding compared to purely matching skills.

Combined Method: After evaluating both approaches individually, the researchers decided to combine them.

They assigned:

- Higher weight to text understanding

- Remaining weight to skill matching

This balanced approach outperformed using either method alone. This clearly demonstrates that both structured skill knowledge and unstructured resume content are essential for accurate career prediction.

## System Architecture:

The system works in several stages:

1.Resume Processing: Work experiences are extracted and organized.

2.Skill Identification: Relevant skills linked to previous roles are collected.

3.Text Understanding: Resume descriptions are converted into meaningful vector representations.

4. Career Scoring: Possible next roles are scored based on similarity.

5.Final Recommendation: A ranked list of predicted future occupations is generated.

Key Contributions:

This research contributes in several ways:

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

It shows that resume text contains valuable information for career prediction.

It demonstrates that even smaller datasets can yield useful results if processed correctly.

It emphasizes the importance of combining skill knowledge with semantic text analysis.

It reduces reliance on very large commercial datasets.

It presents a practical and reproducible prediction process.

Limitations :

Although the system provides good results, there are some limitations:

It does not analyse career gaps or promotion timelines in detail.

It does not consider personal interests or personality factors.

It does not take salary expectations and location preferences into account.

The evaluation is limited to a specific dataset.

Real-time industry demand is not included.

[7] Title: SkillRec: A Data-Driven Approach to Job Skill Recommendation for Career Insights

Authors: This research was conducted by Xiang Qian Ong and Kwan Hui Lim from Singapore University of Technology and Design.

Problem Statement:

In today's fast-changing job market, new tools and technologies appear often. Because of this, the skills needed for a job change frequently.

Many job seekers find it hard to understand:

What skills are needed for a specific job title?

What should they learn before applying?

How can they switch to a new industry?

Usually, people rely on manual research, expert advice, or online forums to find out the necessary skills. This process takes a lot of time and can be confusing, especially for recent graduates or those switching careers.

The main problem this paper addresses is:

How can we automatically suggest the relevant skill sets for a job role using real job market data?

The authors focus primarily on identifying the skills needed for a specific job title.

Methodology:

To tackle this problem, the authors created a system called SkillRec. The system has several stages.

Data Collection: The system collected about 6,000 job listings from online job platforms over six months. These listings include:

Job title

Job description

Required skills

They also gathered 589 unique skill names from online course platforms.

Data Preprocessing: The collected job descriptions were cleaned and processed:

Converted to lowercase

Removed unwanted symbols

Extracted job title and skill information

Skills mentioned in job descriptions were matched with the predefined list of 589 skills.

Job Title Representation: To better understand job titles, the authors used embedding techniques:

BERT embeddings

Fast Text embeddings

These techniques transform job titles into numerical vectors that capture their meanings.

For example, "Software Developer" and "Software Engineer" would have similar vector representations.

Skill Prediction using Neural Network: After converting job titles into vectors, this representation is passed into a feed-forward neural network.

The neural network:

Takes the job title vector as input

Predicts probability scores for 589 possible skills

Uses Sigmoid activation

Uses Adam W optimizer

The final output is a list of recommended skills for that job title.

System Architecture:

The SkillRec system has four major components:

Web Collection Module:

Collects job listings from online platforms.

Data Processing Module

Cleans text and extracts job titles and skills.

Job Title Embedding Module

Converts job titles into vector form using BERT or Fast Text.

Skill Recommendation Module:

Uses a neural network to predict required skills.

The final system outputs a recommended skill set for a given job title.

Key Contributions:

This paper offers several important contributions:

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Introduces a fully data-driven skill recommendation system.

Collectsreal-worldjobpostings for analysis.

Demonstratestheeffectiveness of embedding-basedjobtitle representation.

CombinesmodernNLPtechniques withneuralnetworks.

Achieveshighpredictionaccuracy usingarelativelysimple architecture.

Providesascalablesolutionforautomatedskillguidance.

Limitations:

Despitegoodperformance,thesystemhassomelimitations:

Itonlyconsidersjobtitleasinput(notthefulldescription context).

Datasetsizeismoderate(6,000listings).

Non-technicalroleshavelessrepresentation.

Thesystemdoesnotaccountforindividualbackgroundsor experiences.

[8] Title: AdaptJobRec: Improving Conversational Career Recommendation with an LLM-Powered Agentic System

Authors: This research was conducted by a team from

Walmart Global Tech in partnership with the University of Arkansas. The system was designed and tested using real career data from Walmart.

Problem Statement:

Conversational recommendation systems have improved with the rise of Large Language Models (LLMs). Many now use agent-based structures that can think, plan tasks, and access external tools.

However, a major issue with these systems is response delay. When every question requires complex reasoning, the system slows down, especially for simple requests such as:

Check my application status.

When is my interview?

Show me cashier jobs in Texas.

In a corporate setting like Walmart, users expect quick answers. This paper addresses the main question:

How can we build a conversational career recommendation system that handles both simple and complex inquiries efficiently while reducing response time?

The authors aim to strike a balance between intelligence and speed in a job recommendation chatbot.

Methodology:

To address this issue, the authors proposed a system named AdaptJobRec. The system has an effective method that first identifies ifauserqueryissimpleorcomplex.

Step 1: ComplexityIdentification

When a usersubmitsaquery,thesystemcategorizesitas:

Simple Query

Examples:

Checking job status

Asking for interview information

Searching for job openings

Forthesequeries,thesystemdirectlycallsthenecessarytool without heavy reasoning, which reduces delays.

Complex Query

Examples:

Create a career growth plan for me.

Suggest roles based on my experience and interests.

Forthesequeries,thesystemactivatesadvancedmoduleslike:

Memory processing

Task planning

Personalized recommendation tools

This selective activation cuts down on unnecessary computation.

Step 2: Memory Processing Module

Insteadofblindlyusingtheentirechathistory,thesystem filtersonlytherelevantpartsofpastconversationsusinga few-shot learning strategy.

Thishelpsavoidirrelevantinformation,improveplanner accuracy, reduce unnecessary dialogue rounds.

Step 3: Task Decomposition Planner

Forcomplexqueries,thesystembreakstherequestinto smallertasks.Unliketraditionalplannersthatcompletetasks oneafteranother,AdaptJobRecgroupstasksthatcanoccur simultaneously.

For example:

Count jobs in Seattle

Count jobs in Sunnyvale

Thesetwotaskscanrunatthesametime,speedingup response time.

Step 4: Personalized Recommendation Tools

Thesystemusesalargeinternalknowledgegraphcalled employee which includes job titles, skills, transitions,applicantprofiles.Usingthis,thesystemprovides personalizedJobRecommendations,basedonuserprofile, interests, and behaviour, career Path Recommendations.

Usesshortestpathalgorithmsintheknowledgegraphto suggest career progression.

Step 3: Cypher Query Tools

Convertsuserqueriesintographdatabasequeriesfor flexible information gathering.

System Architecture:

The architecture includes:

Front-end interface

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Backend server

LLM-powered agent

Knowledge graph database

Caching system (Redis)

Streaming system (Kafka)

The workflow is as follows:

User sends query

System retrieves user profile and chat history

Complexity is identified

Simple queries → Direct API tool call

Complex queries → Memory module + Planner + Tool execution

Final response generated

The system is set up as microservices for flexibility and growth.

Result:

Three evaluation tasks were performed:

A) Job Recommendation Task

Compared with:

RAG-based LLM

React agent

Plan & Execute agent

MACRS agent

Results showed that AdaptJobRec had the best performance in:

Hit@10

NDCG@10

MAP@10

It consistently outperformed all baseline models.

B) Career Path Prediction Task

The system was trained using nearly 900,000 real employee transition records.

Compared with:

Frequency-based method

Fine-tuned LLaMA model

Fine-tuned DeepSeek model

AdaptJobRec achieved:

Higher real transition hit rate

Lower response time

This shows it balances accuracy and efficiency.

C) Pilot User Study

A study with 30 users and 150 conversation sessions revealed:

Fewer conversation rounds needed

Faster response time

About 50% latency reduction compared to baseline systems

The improvements were statistically significant.

Key Contributions:

This paper offers several contributions:

Introduces the first conversational job recommendation system with dynamic complexity identification.

Reduces response time by selectively activating agent modules.

Proposes few-shot memory filtering for better context handling.

Develops asynchronous task decomposition to improve speed.

Integrates knowledge graph-based personalized tools.

Demonstrates strong real-world performance using large-scale corporate data.

Achieves significant latency reduction (over 50%) while improving recommendation accuracy.

Limitations:

Despite its strong performance, some limitations exist:

Tested mainly on Walmart's internal data.

Heavy reliance on a structured knowledge graph.

Implementation complexity is high.

Requires substantial computational resources.

Deployment and maintenance costs may be high for smaller organizations.

[9]Title: Personalized Career-Path Recommendation Model for Information Technology Students in Indonesia

Authors: The study was conducted by researchers from Bina Nusantara University and Telkom University, Indonesia. They have expertise in data mining, artificial intelligence, and information systems.

Problem Statement:

Many computer science students struggle to choose a specialization in the IT field. Most rely on advice from friends, seniors, or family instead of structured career guidance. This results in:

Mismatch between personality and career

Job dissatisfaction

Poor academic decision-making

Confusion when selecting elective subjects

Existing recommender systems mainly focus on:

Technical skill matching

But they do not combine:

Academic curriculum

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Industry job demand

Psychological personality assessment

So the main problem this paper addresses is:

How can we build a personalized career path recommendation system that integrates academic subjects, IT job profiles, and personality types to effectively guide computer science students?

Methodology:

The authors proposed a framework called Career Path Recommendation Model (CPRM) based on:

Educational Data Mining (EDM)

Grounded Theory (GT)

Personalized Naïve Bayes (p-NB)

This approach follows mixed-method research combining quantitative and qualitative techniques.

Step 1: Data Acquisition

Three main data sources were used:

IT Job Profiles

Collected using web scraping from job portals

Extracted job titles and required skills

Subject Profiles

Extracted from university curriculum documents

Learning materials were mapped using Grounded Theory

Personality Types

Students completed an MBTI test (52 questions)

16 personality types were identified

Step 2: Job Profile Construction

Text preprocessing including tokenization, stop word removal, and lemmatization

Average Linkage Hierarchical Clustering (ALHC) was used

Skills were grouped into technical competency categories

This helped identify the required skill clusters for each IT job.

Step 3: Subject Mapping

Grounded Theory was applied in three stages:

Open coding

Axial coding

Selective coding

Elective subjects were mapped to specific IT jobs.

Validation was done through:

22 lecturers

10 IT professionals

3 psychologists

Step 4: Personality Mapping (MBTI Integration)

MBTI personality types were mapped to IT job roles.

For example:

INTJ corresponds to research-oriented, analytical jobs

ESFP corresponds to interactive and support roles

Statistical validation involved:

Pearson correlation

Reliability score was approximately 0.703

Step 5: Recommendation Engine

A Personalized Naïve Bayes (p-NB) algorithm was implemented. It calculates:

Prior probability based on MBTI responses

Posterior probability for job likelihood given a personality type

The system then recommends:

Suitable IT job roles

Relevant elective subjects.

System Architecture:

The CPRM framework has four layers:

Data Acquisition Layer:

Collects job, subject, and personality data

Database Layer:

Stores structured job and subject mappings

Functional Layer:

EDM-GT model along with the Naïve Bayes recommender engine

Application Layer:

Web-based interface using ReactJS for the frontend and Golang for the backend

Workflow:

Student takes the MBTI test, system processes via p-NB, and displays job and subject recommendations

Key Contributions:

This paper makes several important contributions:

Proposes a hybrid framework combining

Educational data mining

Grounded theory

Psychological assessment

Integrates academic curriculum with industry job demand.

Validates recommendations with the help of IT professionals and psychologists.

Introduces a personalized Naïve Bayes-based recommender for career paths.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Results:

The model was tested with:

104 students for association analysis

65 students for recommendation quality testing

Evaluation metrics included:

Accuracy

Coverage

Novelty

Diversity Usage

prediction

Key findings indicated:

85% classification accuracy

83% of students agreed that recommendations matched their personality

91% were satisfied with the recommendations

93% diversity was found in recommended jobs

Limitations:

Despite its promise, the model has certain limitations:

Web scraping may lead to incomplete or noisy job data.

The dataset is limited to the Indonesian IT context.

Personality mapping may introduce subjective bias.

Comparison with similar models is limited.

It uses Naïve Bayes, a simple probabilistic model, while advanced deep learning methods were not explored.

[10] Title: Sankalp: AI-Powered Career Guidance System

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Problem Statement:

Traditional career guidance systems have several major limitations. Lack of personalization. Most systems give generic recommendations based only on marks or interests. Limited accessibility. In countries like India, the student-to-counsellor ratio is very high. This makes professional guidance hard to get for many students. Absence of emotional understanding. Conventional systems do not consider the emotional state or confidence level of students when recommending careers. Language barrier. Many platforms are available only in English, which limits their use in rural and regional areas.

Static recommendation models. Traditional systems do not change or improve based on user feedback. Because of these issues, students often make uninformed career choices. This leads to skill mismatch and dissatisfaction. Therefore, there is a need for a scalable, intelligent, multilingual, and adaptive AI-driven career guidance system.

Methodology:

The Sankalp system uses a hybrid multi-agent architecture with the following components:

Semantic Matching using Sentence-BERT (SBERT)

Converts user profiles and career descriptions into vector embeddings.

Uses cosine similarity to match user interests and skills with suitable careers.

Emotion Analysis using VADER Sentiment Analysis

Detects the emotional tone (positive, negative, neutral).

Adjusts the response style to offer empathetic guidance.

Rule-Based Reasoning Engine

Applies academic eligibility rules and domain constraints.

Ensures logical and clear recommendations.

Reinforcement Learning (RL) Adaptive Layer

Learns from user acceptance or rejection of suggestions.

Dynamically improves recommendation accuracy over time.

Knowledge Graph Module

Connects careers, skills, subjects, and personality traits.

Provides clear and related career suggestions.

Multilingual Voice Assistant

Supports English, Hindi, and Kannada.

Uses Speech-to-Text and Text-to-Speech services for voice interaction.

Real-Time Job Market Integration

Retrieves trending job data to align recommendations with industry demand.

The system was tested using 160 participant profiles and validated against a Curated Ground Truth dataset.

Key Contributions:

Introduced a hybrid AI-based career guidance framework that combines rule-based logic, semantic similarity, and reinforcement learning. Integrated an emotion-aware recommendation system for empathetic interaction. Developed a multilingual and multimodal platform that supports voice and text input. Implemented a Knowledge Graph for clear explanations, improving user trust.

Results:

Top-3 Hit Rate of 90.5%

Top-1 Hit Rate of 77.5%

Mean User Satisfaction Score of 4.71/5

Designed a scalable system suitable for developing countries that face a shortage of counsellors.

Limitations:

Dependence on cloud services may increase latency and cost.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Translation-based sentiment analysis may slightly reduce emotional accuracy in regional languages.

Rule-based constraints may limit flexibility in rare or unconventional career paths.

External expert validation was limited due to time and resource constraints.

Large Language Models (like GPT) were not fully integrated due to computational and ethical considerations.

Proposed System:

The proposed system is an AI-Based Career Recommendation and Guidance Platform designed to help students and job seekers choose the right career path based on their individual profiles. Many students feel confused after finishing school or college because they are unsure which career fits their skills and interests. This system aims to solve that problem with smart data analysis and machine learning techniques.

In this system, users first register and create a profile. The platform gathers important details like academic background, resume, area of interest, strengths, and career goals. It also conducts aptitude tests and technical skill assessments to gauge the user's logical ability, problem-solving skills, and domain knowledge.

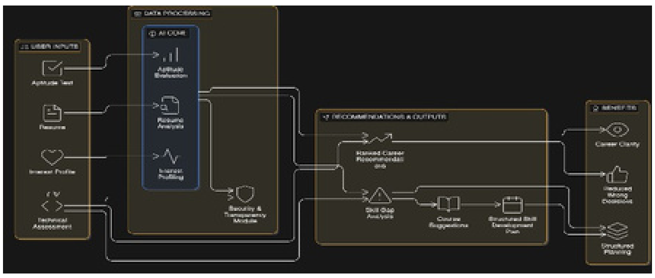
After collecting the data, the system analyses it using AI algorithms and compares it with a structured career database. Based on the user's performance, interests, and skill level, the system generates personalized career recommendations. Instead of offering general suggestions, it provides specific career roles that match the user's profile.

The system recommends suitable job roles and suggests the courses, certifications, and skill development programs needed to reach that career. If a user shows interest in a particular field, the platform provides a roadmap with learning paths from beginner to advanced levels.

Additionally, the system continuously improves its recommendations by learning from user interactions and feedback. This makes the platform more precise and personalized over time.

The proposed system reduces confusion in career decision-making, saves time, and offers structured guidance. It acts as a smart career mentor that helps students make informed and confident career choices.

**System Architecture:**




**Methodology:**

Collection of User Information:

In this system, the first step is to understand the user well. When a student enters the platform, they create an account and provide their academic details, skills, interests, and career choices. The system also allows users to upload their resumes to identify additional skills and experiences.

Besides basic details, users take aptitude and technical tests. These tests measure logical thinking, analytical ability, and subject knowledge. This helps the system avoid giving random suggestions and instead offer meaningful guidance.

Organizing and Preparing Data:

After collecting the details, the system carefully processes the information. The resume is scanned to identify important skills and keywords. Unnecessary information is filtered out. Test scores are arranged in a standard format for easier comparisons. This stage ensures the data is clear and relevant, making it ready for analysis.

Profile Analysis:

Once the data is prepared, the system analyses the user profile in detail.

It checks which domain interests the user most, where their performance stands out, and what skills they have. These factors are turned into measurable values so the system can compare them with career roles available in the dataset.

Career Matching:

In this step, the system compares the user profile with various career options stored in the database. A matching score is calculated based on skills, interests, and performance. Careers that closely match the user's profile are shortlisted.

Instead of providing too many options, the system focuses on the most relevant career paths to reduce confusion.

Providing Career Guidance:

After identifying suitable careers, the system shows the results to the user. Along with career names, it explains:

- What skills are required
- What certifications can help
- What courses should be completed
- What steps should be followed in the future

This makes the platform serve as a digital career mentor.

Continuous Improvement:

The system also takes user feedback into account. If users engage more with certain recommendations or provide feedback, the system learns from it. This helps improve accuracy over time.

Implementation:

User Interface Development:

The system is implemented as a web-based platform. The front end is designed to be straightforward, allowing students to register, fill out forms, upload resumes, and take tests without confusion. The interface aims for clarity and smooth navigation.

Server-Side Processing:

Thebackendmanagesallkey operations. When the user submitsinformation,theserver processes the data, extracts skills, calculates test results, and prepares the profile for matching.Italsohandleslogin authentication and securely stores user data.

Data Storage:

Alluserinformation,testquestions, career datasets, and coursedetailsarestoredinastructured database. This allows quickaccesstoinformationwhenever recommendations are generated.

IntegrationofIntelligentModel:

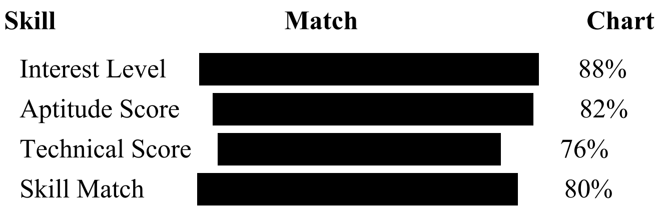
Amachinelearningmodel is trained using career and skillmappingdata.Whenauser completes their profile and assessments,themodelevaluates the details and predicts suitable career options.

Themodelconnectswith the back end to generate recommendations instantly.

Testing and Validation:

Beforedeployment,thesystem is tested with various user cases.Theaccuracyofrecommendations, speed of processing, andcorrectnessofoutputsareverified. Any errors identified duringtestingarefixedtoimprove system reliability

**Chart:**




**Result:**

| Test Category | Score | Suggested Field |
|---|---|---|
| Aptitude Test | 82% | Data Analytics |
| Technical Test | 76% | Software Development |
| Interest Analysis | 88% | UI/UX Design |
| Skill Match | 80% | Product Design |

**Conclusion:**

The AI-Based Career Recommendation and Guidance System aims to help students and job seekers navigate their career choices. Many people choose careers without fully understanding their strengths, interests, and abilities. This often leads to dissatisfaction and changes later on. The proposed system seeks to address this problem by offering organized and personalized guidance.

By gathering user information like academic background, skills, interests, and assessment results, the system builds a detailed profile of each individual. Instead of offering general advice, it carefully examines the data and suggests career options that closely align with the user's abilities. Along with job role recommendations, the system also shares information about necessary skills, certifications, and learning paths, making it more practical and useful.

Using machine learning techniques improves the recommendations' accuracy. As more users interact with the system and give feedback, it can keep improving. This allows for better performance over time.

Overall, the proposed system serves as a smart digital career mentor. It aids in making informed decisions, saves time, and helps users confidently pursue their professional goals. With further improvements and real-world data integration, the system has strong potential for use in schools and career guidance centres..

**References :**

[1]A Career Recommendation Method for College Students Based on Occupational Values — Lei Wang, Yuanyuan Fu, Yingchao Zhang (2023)

[2]A Machine Learning-based Career Recommendation — Vaishnavi Nayak & Neha Vora (2024)

[3]Personal Career Recommendation System — Chaganti Revanth, C. Venkata Yaswanth, Divya B., K. Sai Sumanth Reddy, Veena M (2023) [4]Career Recommendation System — Mohd Vakil, Sanjeev Kumar, Anjali Yadav, Suraj Singh, Khushi Garg (2025)

[5]Career Recommendation System (Engineering Streams WebApp) — Snehal Joshi, Manasi Jadhav, Pratiksha Londase, Sakshi Nikat (2023) [6]Career Recommendation System Using KNN — Ameya Pasare, Shreya Khupse, Priyanka Jadhav, Kshitij Habbu (2024) [7]AI-Powered Career Recommendation System — Akash Vishwakarma, Prakhar Gupta, Karan Yadav, Viru Rajbhar, Ashish Kumar Yadav (2025) [8]Educational Career Recommendation System Using Machine Learning — Sushma Koushik N et al. (2021)

[9]Career Counselling Recommendation System (Preprint) — Mehul Kumar, Aryan Raj, Sandeep Kumar (2025)

[10]A Hierarchical and Multi-Tiered Personalized Career Recommender System — (Published 2025)

[11]AI-Driven Career Guidance System: A Predictive Model for Students — Pranjali Bahalkar, Prasadu Peddi, Sanjeev Jain (2024) [12]Career Recommendation Based on Feature Selection — (Published 2024)

[13]Unlocking Futures: A Natural Language Driven Career Prediction System for CS Students — Sakir Hossain Faruque, Sharun Akter Khushbu, Sharmin Akter (2024)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

[14]SkillRec: A Data-Driven Approach to Job Skill Recommendation for Career Insights — Xiang Qian Ong & Kwan Hui Lim (2023)

[15]Personalized Job Search with AI: Skill Based Matching — Ch. Raja Kishore Babu, Tusyaa Sreerala, Ritesh Kumar, Siddamshetti Sumith (2025)

[16]Career Recommendation System for Scientific Students Based on Ontologies — Alimam Mohammed Abdellah, Alimam Mohammed Karim, Seghuiouer Hamid (2019)

[17]Using Recommendation System to Help Students Choose a Career Based on Interests — Shivendra Saurav et al. (2020)

[18]Recommender System for Career Guidance and Counselling — (ResearchGate paper, various authors) (2023)

[19]Career-Based Project Recommendation System — Smitha Vas P et al. (2025)

[20]A Systematic Review of Recommender Systems for Student Academic and Career Guidance — Mahmoud H., Badouch M., Boutaounte M., Zioudi O., Boulmane E.S. (2025)\