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Design and Development of an AI-Powered Student Career Navigation Platform

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Abstract: It's obvious that moving from school or college to a job often shows a big gap between what students can do and what they hope to achieve, and what the job market needs in terms of clear and tailored support. The project introduces NextStep Navigator, a platform focused on helping students with their career choices.It takes information from users, like their resumes or questions about careers, and uses that to create tailored and useful career suggestions. The system is designed to smartly analyze resume information by applying advanced methods to identify specific skills related to a field, areas of interest, and realistic salary expectations, which helps in building a detailed user profile. Based on this profile, the platform will follow a clear step-by-step process to figure out how much the user is interested in getting a job right away. If a career-focused direction is found, the system suggests related jobs, internships, and carefully selected learning materials like valuable YouTube videos. All the suggestions and materials are displayed on a personal dashboard that also tracks the user's progress and has a special chatbot for quick, customized help with student questions. The main goal is to connect a student's education, their future job plans, and available job chances in a clear way.This helps each student get personalized support that matches their specific goals and abilities. This study helps create a model that can be used widely and works well to improve career preparation by using smart data handling and tailored digital support.

Keywords: data-driven career planning, resume parsing, personalized recommendation system, career assistance, job search platform, educational resources, chatbot, and decision-making flow.

I. INTRODUCTION

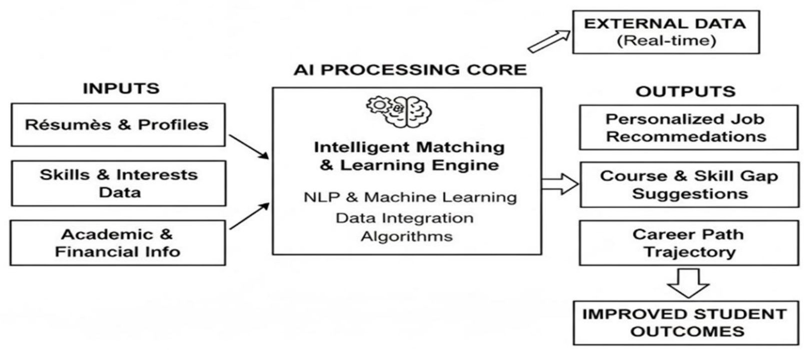
In recent times, the fast-changing world of education and work has created a strong need for better organized and tailored career guidance systems. Moving from school to work can be tough, and it often brings feelings of uncertainty about whether your skills are useful, how to apply them, and where your job path might lead. Good career advice should cover many areas and work together with a person's skills and the current job market opportunities. The use of Artificial Intelligence in this area is quickly changing how traditional guidance works, making it possible to provide support that is both scalable and very tailored to individual needs.Career choices are a natural but complicated process that brings together many factors like academic results, personal interests, abilities, and financial aims. Traditional guidance models usually give general advice or require manual checking of resumes, but the tools used for these tasks often don't offer detailed, useful, and customized suggestions that are necessary for successfully competing in today's job market. Thanks to recent advances in Natural Language Processing (NLP) and machine learning, it's now easier for these systems to analyze complex, unstructured data like resumes or query logs to find hidden career clues.

Even though there have been big improvements in general recommendation systems, like those used in e-commerce and media, the area of personalized career planning is still not well developed.This kind of system would smartly combine different types of information, such as skills, interests, and data about the job market, but it hasn't been widely explored yet. Textual document intelligence parsing, like analyzing resumes, is important for data analysis to improve the accuracy of personalized AI systems. Domain expertise, desired salary, and the choice between starting a job right away or continuing education are all key influences on a student's career decisions and are clearly shown in their application materials and questions.

The growing amount of digital information about job listings, professional social media, and online learning materials opens up new opportunities for smarter career-focused systems to help students succeed better. The main problems with traditional models are that they work with just one kind of input, like a basic survey or a small job list, and they don't do a good job of linking a student's specific background with good, suitable opportunities because it's hard to understand the right context and match skills properly. New progress in natural language processing and machine learning has allowed combining different types of data and building systems that better understand users in a more complete and efficient way.

Modern career theory says that a good career path comes from how a person's sense of self and the outside world around them work together. Some other researchers have taken these ideas and applied them to more complicated things like how satisfied people are with their lives and how well they can bounce back in their careers. The skills a student has, the things they care about, and what they expect to earn all show how ready they are for a job.But among all the documents used when applying for jobs, the digital resume is the one that is used the most. Career guidance based on resumes doesn't capture the details of in-person advice, so it's harder to understand someone's skills accurately, match job chances with the right context, and deal with different personal goals. Many methods have been developed that use machine learning and deep learning to help match students with jobs.These methods include things like collaborative filtering and content-based techniques, and they have been successful in making good recommendations. However, there are challenges like not having enough vocabulary related to jobs, not fully understanding the meaning of job descriptions, and not being able to get useful information from student profiles. More and more, hybrid and transformer-based models are being used to solve these issues, which helps make career suggestions more accurate and relevant in different job markets.

Figure 1: Overall architecture of the data flow and core components for the proposed system



A. *Motivation Behind the Project*

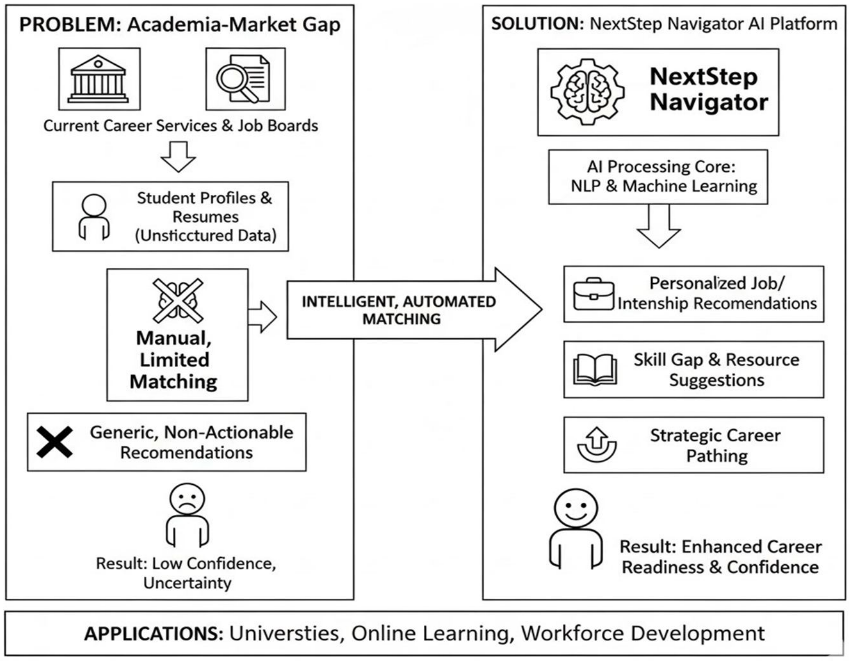
The current job market is getting more complicated and fast-changing, with quick updates in technology and new needs for skills. So, in reality, people need ongoing and highly tailored career advice. This research is driven by the important need to create a smart, data-based system that connects a student's individual academic background and future goals with real job opportunities that match what the market needs.The goal is to help students become more prepared for their careers and feel more confident in their choices. Most job boards and university career services today can't handle complex, unstructured information like resumes well, leading to vague suggestions or time-consuming manual processes.

The NextStep Navigator technology is designed to solve this important problem by automatically and smartly understanding what the user is looking for in their career.It uses various types of input, especially from the resume and direct questions, to figure out the user's professional goals. This system uses advanced NLP and machine learning, along with organized career guidance methods, to give very relevant and customized suggestions for jobs, internships, and helpful resources. The expert intelligence will help the platform serve as a constant, unbiased career guide by offering timely advice, checking if skills match job requirements, and suggesting learning paths to cover any missing skills.

This project also highlights one of its main goals: connecting academics with the market. This system is built to give detailed and tailored support, unlike typical task-focused assistants or basic keyword-based job platforms. It can be used in university career centers, online learning websites, and programs that help people develop their jobs. This new idea will bring together AI, education technology, and human resource management.

The remaining part of the paper is structured like this: Section II covers related works and provides background information on intelligent career guidance systems and recommendation engines. Section III explains the NextStep Navigator model and how it processes data. Section IV covers how the system was put into action, the outcomes from the system, and how well it performed. Finally, Section V wraps up the paper and gives an idea of where future research might go.

Figure 2: Motivation and Conceptual Framework of the Navigator System.



II. LITERATURE REVIEW

Career guidance technology and recommender systems have, since the rise of deep learning, focused on personalized and data-driven approaches. This part looks at the latest important research in major technical areas and points out the missing pieces that make a focused, student-friendly career advice system necessary.

A. Resume and Document Parsing

Intelligent document processing has quickly advanced, especially when it comes to resumes and CVs.Recent surveys have shown how much progress has been made in techniques such as named entity recognition, section segmentation, and skill extraction, using models like CNNs and transformers. More modern workplaces focus a lot on solving problems related to data differences, like varying resume formats and messy text, and unfair treatment based on identity.They also suggest better ways to build systems and train models so they can work well in real life, especially when pulling out specific skills and work history from different fields.

B. Career Path and Skill Gap Analysis

Career path modeling keeps getting better by using deep learning methods that look at sequences.These methods mix skill sequence learning, like skill embeddings, with time-based models such as LSTMs or Transformers, and attention mechanisms.This helps predict the next role someone might move into or find out where their skills are lacking. Recent studies show that using hybrid models combining CNN and LSTM, or models with enhanced transformers, makes systems better at dealing with noisy data in career history and managing complex relationships between skills.However, applying these models across different fields, like from IT to Finance, is still difficult. These improvements encourage the use of strong skill matching and gap checking in a customized career tool.

C. Job and Internship Recommendation Systems

Recent job recommendations have greatly focused on transformer-based models that understand context, like BERT, RoBERTa, and similar models, as well as methods that adapt these models to specific fields. Studies since 2020 show that contextual embeddings do much better than traditional keyword matching and collaborative filtering methods when working with data from the same domain.However, they still have problems with generalizing to new areas and handling new users or new jobs, which limits their use in real-world situations. Approaches like adjusting the model for specific tasks, combining it with knowledge graphs, and using multi-task learning (like for recommendations) are used.

D. Decision-Making and Personalized Guidance Platforms

Since 2020, a series of studies has shown that these hybrid systems, which mix user data with clear decision rules like preferring full-time jobs over internships or setting a minimum salary, perform better than simpler recommendation methods that rely only on hidden factors.They do this by picking up on different signals that show what users really want. Recent surveys and reviews have come out that bring together the main ways hybrid systems combine rule-based approaches with machine learning results and personalization techniques. In practice, there are challenges like understanding unclear intentions, creating detailed models of user preferences, and explaining recommendations clearly. These studies clearly support a mixed method that takes intent into account when creating real, useful guidance agents.

E. Conversational AI in Education and Career Counseling Conversational

Studies have looked into using agents and virtual assistants, like specialized tutoring bots, to make student support and answering questions more scalable. Studies with real users show that there are advantages like better access, quicker responses, and less work for administrators. Recent studies also point out issues like incorrect technical details, not enough background in answers, and the need for strong knowledge sources to avoid spreading wrong information.This pushes for careful planning and clear limits when using these systems.

F. Open Problems and Research Gap

Recent studies point out three main areas that still need improvement for this work: first, there's a need for strong, personalized career planning that goes beyond just moving from one job to another.It should include educational tools and ways to build skills, with clear steps someone can take.Second, there's no clear process for making decisions that takes in student data like skills, salary, and goals, and turns it into easy-to-understand advice.Third, there's a lack of a complete platform that brings together advanced resume analysis, recommendations in different formats like jobs, internships, and videos, along with support all in one place. These gaps lead to our proposed NextStep Navigator platform, which uses transformer-based profile understanding, a structured decision-making system, and a personalized dashboard that tracks progress.

Table 1: Comparative analysis of existing career guidance platforms highlighting the feature gaps addressed by NextStep Navigator.

Feature	Gaplify	Cuvette.tech	Skill Gap	LinkedIn	iMocha	Fuel50	Disco
Resume/Domain-Based Analysis	Yes	Yes	Yes	Yes	Yes	No	No
Skill Gap Detection	Yes	No	Yes	No	Yes	Yes	No
Personalized Learning Paths	Yes	No (Paid only)	Yes	No	Yes	Yes	No
Job & Internship Recommendations	Yes	Yes	No	Yes	No	No	No
Higher Studies Suggestions	No	No	No	No	No	No	No
Progress Dashboard	No	Yes	No	Yes	Yes	Yes	No

Feature	Gaplify	Cuvette.tech	Skill Gap	LinkedIn	iMocha	Fuel50	Disco
Integrated Chatbot Support	No	Yes	No	Yes	Yes	Yes	Yes
Student-Centric Design	Yes	No	No	No	Yes	No	No
Real-Time Recommendations	No	No	No	Yes	Yes	Yes	No
YouTube Channel Suggestions	No	No	No	Yes	No	No	No

Table 2: Comparison showing how NextStep Navigator addresses key gaps in existing career guidance systems.

Aspect	Existing Systems & Papers (Yes/No/Details)	Covered in NextStep Navigator (Yes/No/Details)
Existing Systems & Papers	Yes (Covered, as indicated by $\checkmark$)	Yes (Covered in NextStep Navigator, as indicated by $\checkmark$)
Explainable Recommendations	No (Mostly black-box models)	Yes (Transparent, logic-based paths)
Fairness & Bias Mitigation	No (Limited or absent)	Yes (Built-in fairness-aware algorithms)
Counterfactual Career Paths	No (Not modeled)	Yes (Multiple "what-if" scenarios)
Student-Centric Design	No (Generic or enterprise-focused)	Yes (Tailored for student needs)
Higher Studies Guidance	No (Rarely included)	Yes (Integrated suggestions & pathways)
Real-Time Recommendations	No (Static or delayed)	Yes (Dynamic, adaptive suggestions)
Integrated Dashboard	No (Fragmented or missing)	Yes (Unified progress tracker)
YouTube Guidance	No (Not supported)	Yes (Curated content & channel links)

III. PROPOSED METHODOLOGY

The NextStep Navigator system will use a step-by-step approach that includes machine learning and deep learning to turn user input into useful, personalized career advice. Each main part of the system gives special information that comes together to give a full picture of the user's job background and what they are looking for. It has three main parts: one that handles resume information, one that understands what the user is looking for, and the Recommendation and Fusion part, which combines all the results to give career suggestions and tailored answers.

A. Loading Dataset and Libraries

Three different main sets of data are already loaded for resume text, job listings, and user activity records. The information comes from special sources and public databases, such as Kaggle's resume and job data sets, as well as labor statistics from government organizations.

1) Resume Dataset: This dataset includes many thousands of resumes that have been made anonymous, and each one is marked with the skills, experience levels, and job titles they are looking for.
2) Job Posting Dataset: This dataset includes organized job descriptions that are marked with the skills needed, the pay range, the industry it's in, and the job type, like full-time or internship.
3) User Interaction Logs: This includes past user questions and how they've used the platform, and each entry is marked with the user's career goal, like looking for a job, learning new skills, or just being curious.

Each dataset is loaded in either .csv or JSON format and is pre-processed using tools like NumPy, Pandas, Scikit-learn, TensorFlow, Keras, and the Hugging Face transformers library.

B. Data Preprocessing

Preprocessing is carried out to make sure the quality and consistency are the same across all the different types of data.

1) Resume Text Data: Data cleaning gets rid of unusual characters, URLs, and extra spaces. Tokenization and lemmatization are done with tools like NLTK or SpaCy. The dataset is divided into two parts: 80% for training and 20% for testing to check how well the model works. The text is then converted into contextual embeddings by using pre-trained transformer models like BERT or RoBERTa. The dataset is divided into two parts: one for training the model (80%) and one for testing its performance (20%).
2) Job Posting Data: The sample rate is set and agreed upon to properly show the skills involved. The features that were pulled out are the necessary skills, the names of the companies, and the salary ranges. Textual sections like job descriptions are turned into vector forms using the same transformer embeddings, so they can be compared directly with the vectors from resumes.
3) User Query Data (Chatbot Input): Data augmentation methods are used to help the model perform better when dealing with different types of questions. After that, the queries are checked to figure out what the user is looking for.For example, if someone asks "Find an internship," it's classified as Job-Oriented. If they ask "What is Machine Learning?" it's considered Information-Seeking.

Characteristic	Resume Text Data	Job Posting Data	User Query Data
Data Cleaning	Removes non-standard characters	Sample rate fixed	Data augmentation applied
Text Processing	Tokenization and lemmatization	Transformer embeddings used	Intent classification performed
Model	Transformer models used	Transformer embeddings used	Intent classification performed
Data Split	80/20 training/testing split	Features extracted	Intent classification performed

Table 3: Data Preprocessing Across Modalities.

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C. Recommendation and Fusion Layer:

The Fusion Layer takes the classified intent and the ordered list of jobs or resources and puts them together to give a full and complete result.

1) Personalized Dashboard: Shows the top k suggested jobs based on the highest similarity scores and displays the gap between the user's skills and the job market. When the similarity score is low or the intent is focused on learning new skills, the system suggests specific resources from YouTube or courses that match skills that are in high demand but are missing.
2) Chatbot Integration: A separate knowledge-based chatbot uses the extracted skills (S) and intent (I), and if needed, the ranked list of jobs or resources, to provide answers that are relevant to the user's situation; for example, "What salary should I expect in my field?"

This method lets the system turn messy, unorganized career information into clear, organized data with importance levels and useful next steps, making sure the advice is highly personalized and relevant.

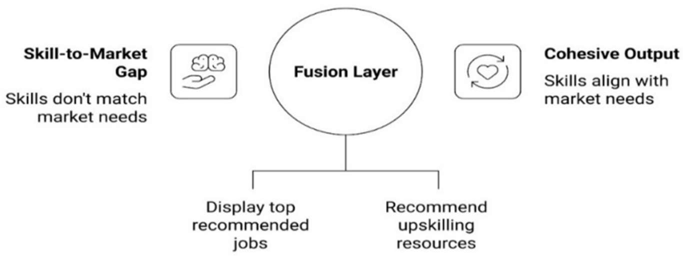

Figure 3: Fusion Layer of the Navigator System.

D. Experiment Design

In order to check the ability of the proposed NextStep Navigator system to give personalized career recommendations based on resumes, an experiment was performed, and details are provided below:

1) System architecture

The system is developed as web-based application which includes user frontend and backend recommendation engine.

2) Development environment:

Development environment for the system development is given below:

- Web Framework: Flask
- Database: SQLite
- Programming language: Python
- Data processing libraries: Pandas, NumPy
- Machine learning library: Scikit-learn
- Application type: web-based recommendation system

3) Input data

Input data for the system is provided by resume documents in PDF format. Other than resumes, different datasets containing information about job opportunities, internships, domains, and educational resources are used.

4) Resume parsing

Resumes that are provided to the system are parsed in order to obtain skillset and domains of interest of the users.

5) Recommendation generation

Personalized recommendations for careers, internships, and educational resources are made by using skills provided by resumes. TF-IDF and cosine similarity measures are used for ranking purposes.

6) Real-time information retrieval

Real-time job opportunities and educational resources are fetched by using APIs

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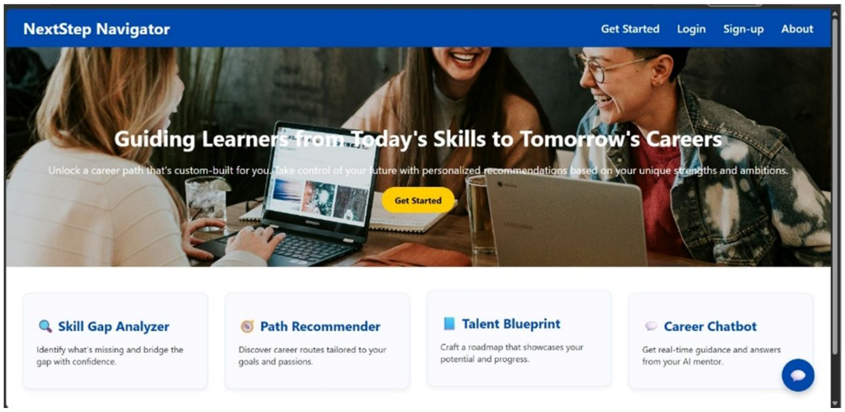
IV. SYSTEM IMPLEMENTATION AND RESULTS

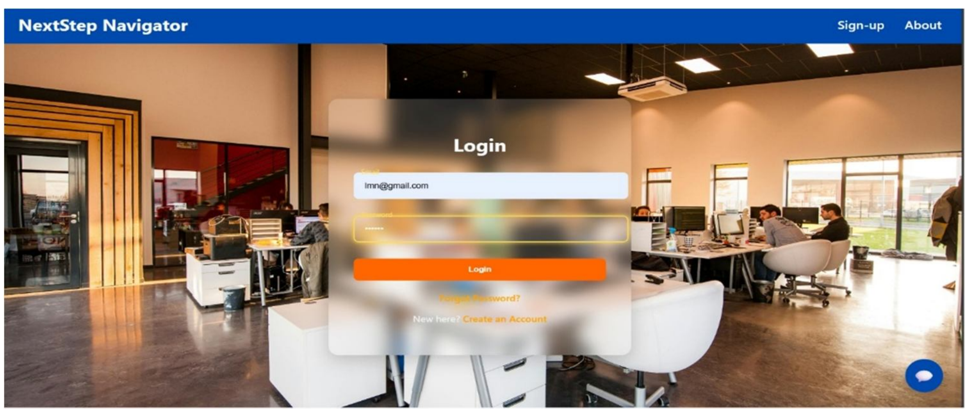
1) *Figure 1: Home Page*

This is the home page which gives a brief introduction about NextStep Navigator Platform along with its salient features like Skill Gap Analysis, Career Path Recommendation, Roadmap Generation and AI Career Guidance.



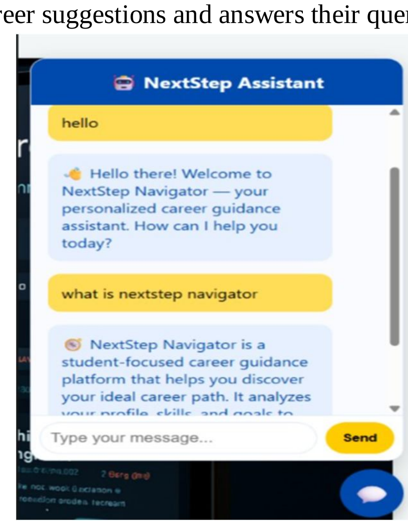
2) *Figure 2: Login Page*

The login page allows registered users to access personalized career suggestions and services available on the NextStep Navigator application.



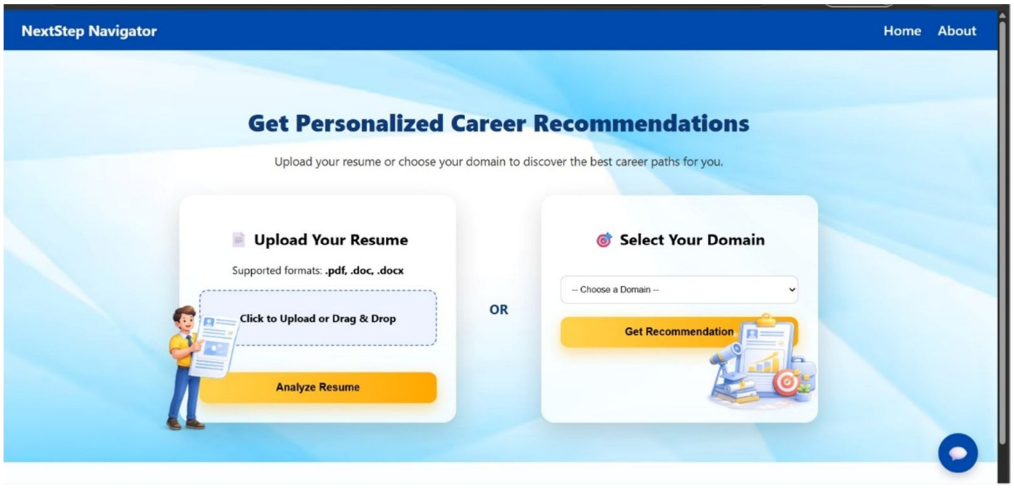
3) *Figure 3: AI Career Chatbot*

An AI chatbot helps users get personalized career suggestions and answers their queries related to career planning.



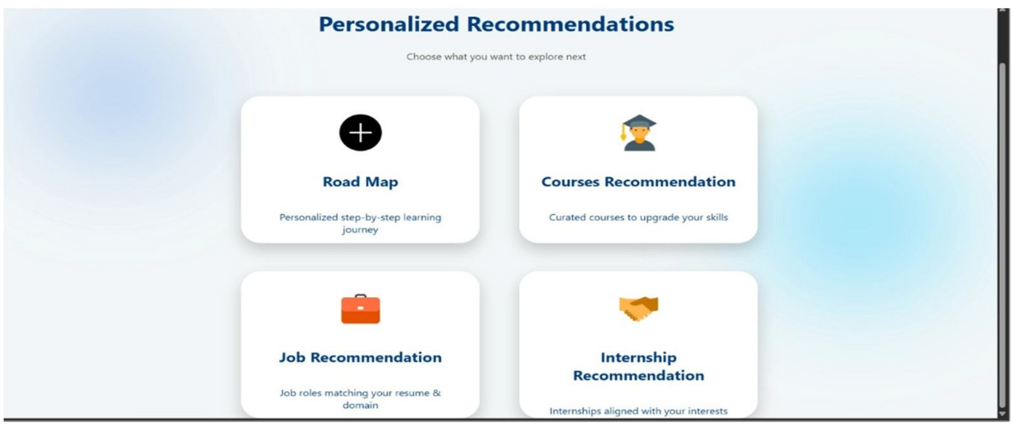
4) *Figure 4: Resume Analysis & Domain Selection*

This page helps users upload their resume or choose a preferred domain to get personalized career suggestions.



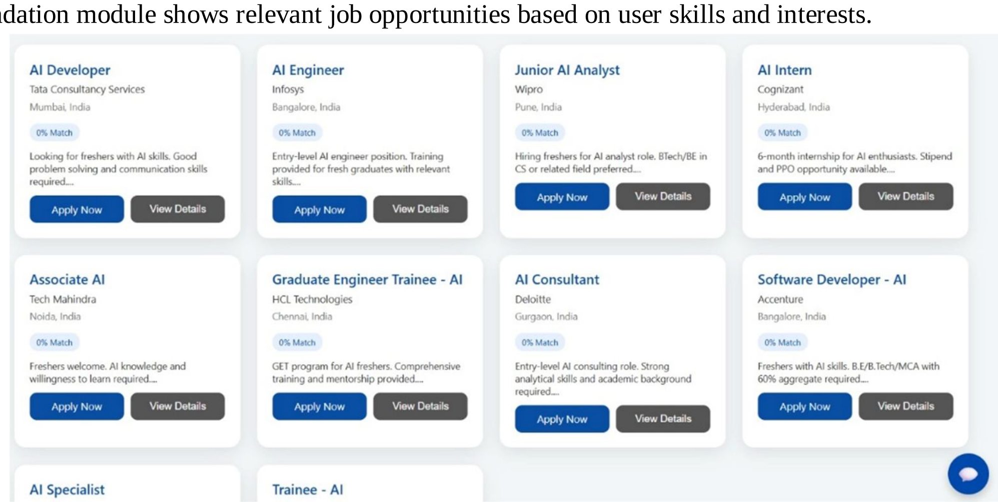
5) *Figure 5: Recommendation Dashboard*

This dashboard includes personalized career learning roadmaps, personalized course suggestions, job opportunities, and internship suggestions according to user profile.



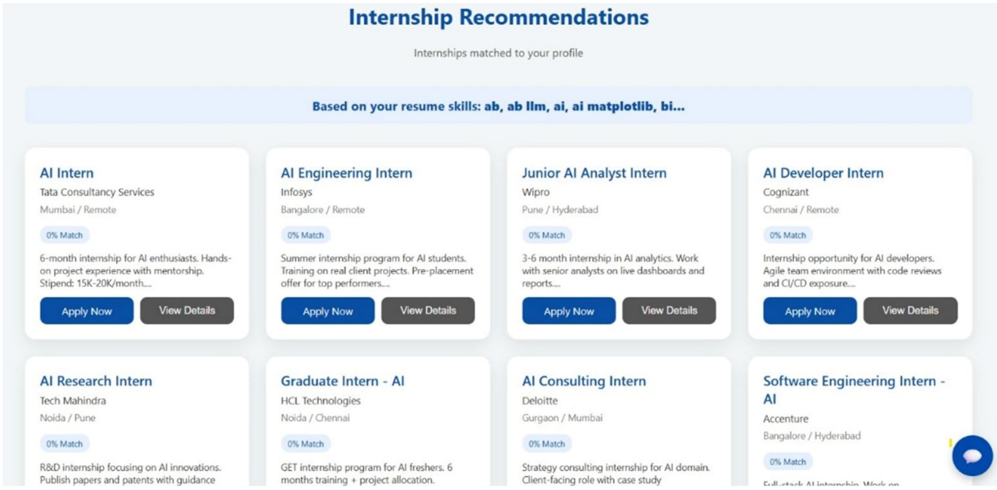
6) *Figure 6: Job Recommendation Module*

The job recommendation module shows relevant job opportunities based on user skills and interests.



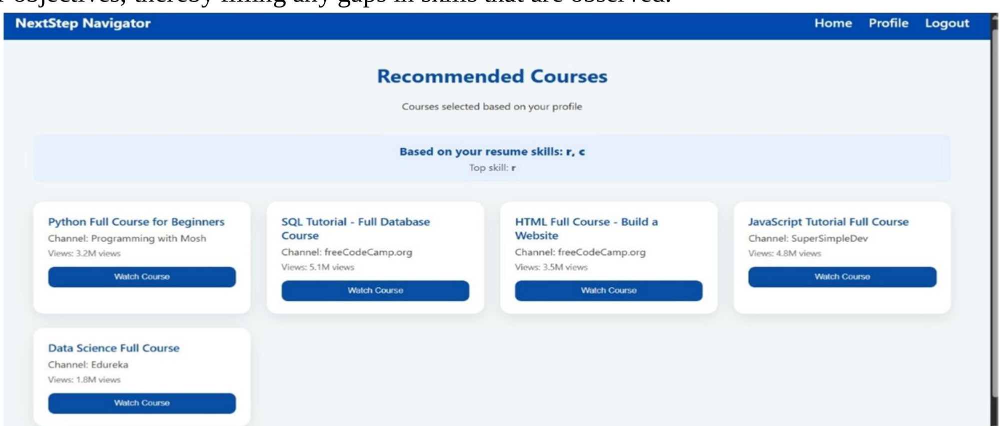
7) Figure 7: Internship Recommendation Module

The internship recommendation module shows relevant internship opportunities for the user.



8) Figure 8: Course Recommendation Module

The course recommendation module recommends personalized study materials and courses depending on the user's extracted skills, interests, and career objectives, thereby filling any gaps in skills that are observed.



A. Experimental Results and Performance Evaluation

To evaluate the effectiveness of the proposed NextStep Navigator platform, the key functional modules, such as resume analysis, skills extraction, career recommendation, internship recommendation, roadmap generation and AI chatbot assistance were tested. The system was tested using several sample resumes from various domains such as Artificial Intelligence, Data Science, Web Development, and Software Engineering.

Table 3 :The average response time recorded for different operations

Operation	Average Time
Resume Upload & Analysis	2.3 seconds
Skill Extraction	1.8 seconds
Job Recommendation Generation	1.5 seconds
Internship Recommendation Generation	1.4 seconds
Roadmap Generation	2.0 seconds
Chatbot Response	1.2 seconds

V. LIMITATIONS

Even though the results look good, the system still has several issues to deal with.

1) Variability in Resume Data: Real-world resume data used to train and test systems may not cover all the different ways people write resumes, including various language styles, cultural differences, and unusual formatting.This can affect how well the system can accurately identify skills and understand the purpose of the documents people submit.
2) Market Data Latency: Job and internship suggestions depend a lot on how up-to-date the information is from outside sources like job listings and company websites. If there is a delay in updating the data, it can result in recommendations about opportunities that have already been closed or are no longer valid.
3) Contextual Skill Misinterpretation: Misunderstanding skills based on how they are described can happen.For example, if someone says they are "familiar with X" instead of "expert in X," it might lead to an incorrect assessment of their abilities.Skills learned outside of school or transferable skills from jobs that aren't traditional can also be misread or not valued properly, which could make someone's actual skills seem less than they are.
4) Bias in Recommendations: The recommendation system might pick up on biases from the training data, like past hiring patterns that favor certain groups for specific roles, without meaning to.This can lead to unfair outcomes, so it's important to keep checking and fixing these issues regularly.
5) Handling unclear user goals: Even when the system tries to figure out if a user is looking for a job or more education, some people might have mixed or changing goals.These can get oversimplified by the system's structured process, leading to recommendations that aren't fully matched to their needs.
6) Ethical and transparency concerns: The issues might come up if the system doesn't clearly explain why it suggests one thing instead of another. To address this, the personalized dashboard should offer clear reasons for each recommendation, and the data handling process should be open and honest.

VI. FUTURE IMPLICATIONS

This project shows how a smart, data-based platform can be a really helpful and scalable tool for supporting students during big career changes and their professional growth. Future developments may also include:

1) Adaptive Recommendation Learning: The system will use context-aware reinforcement learning to keep improving its recommendation strategies based on user interactions, feedback like whether a job application was successful or not, and how their career is actually progressing.
2) Expansion into Global Markets: The platform will grow to include support for multiple languages, allowing it to gather job market information from around the world.This helps people from different countries find job opportunities and move their careers globally.
3) Integrated Skill Certification: The system will connect with top MOOCs or professional certification platforms, making it easier for students to sign up for courses that help fill any skill gaps that have been identified.
4) Predictive Modeling of Career Trajectory: Creating predictive models to forecast long-term career success and salary increases, using data from initial job placements and how much users engage with recommended resources.
5) Deployment as a University/Institutional API: The main part that does the parsing and gives recommendations can be provided as an API.This API can be connected directly to the career service websites of universities, helping to offer better support that is tailored to each specific institution.

VII. CONCLUSION

Creating an AI-driven student career guidance system is a major achievement in developing a smart, well-structured, and easy-to-use platform that helps students with their career choices. Creating systems that turn messy, unstructured information from users, such as resumes, lists of skills, and questions about careers, into clear and useful insights helps connect what people are capable of with real job opportunities. The platform automatically finds skills, determines areas of expertise, and looks at what each user likes.This helps give them tailored suggestions, whether they're looking for a job or an internship. Even though the project is still in the early stages of development, it shows clear potential to be both feasible and scalable. In the future, extra features like machine learning and job market analysis can be added because the system is built in a way that makes it easy to add new parts. Overall, it provides a clear understanding of how technology can make career planning easier for students and help them make confident and informed choices about their future work path.