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CareerSage: A Multi-Phase Transformer-Based Framework for Semantic Career Reasoning and Skill Gap Analytics

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Abstract

Career choice forms one of the key steps in shaping a professional journey, which in turn can determine long-term success. In this fast-changing job environment, many people are caught off guard by not being able to make the right career choices that best fit their skills, interests, and goals. This paper introduces CareerSage: A Multi-Phase Transformer-Based Framework for Semantic Career Reasoning and Skill Gap Analytics that makes this process simpler through smart, flexible recommendations. *CareerSage* requires detailed information like educational background, technical skills, experiences, and objectives to make the guidance more relevant than is possible through typical aptitude tests or job portals. Other platforms, like LinkedIn Learning, Coursera, or AICTE Internship portals, are either learning resources or job listing platforms. At the same time, *CareerSage* integrates skill development, education, and career advancement as one solution. This system utilizes Generative AI combined with semantic reasoning to gain a better understanding of the users and their skill pathways. It identifies gaps in skills using hybrid machine learning models combined with semantic analysis and cosine similarity, suggesting customized learning opportunities originating from trusted sources like SWAYAM and NPTEL. The AI-driven workflow with industry trends evolves; thus, *CareerSage* can help users make intelligent and future-ready choices for their careers.

Keywords: AI-Driven Career Guidance; Personalized Recommendation System; Generative AI; Skill Gap Analysis; Semantic Reasoning; Adaptive Learning; Career Path Prediction; Intelligent Decision Support

1. Introduction

Career choices are significant and play a vital part in the professional journey of a person. They clearly have an impact in the long run, financial stability, and further growth opportunities. Definitely, in today's fast changing job market constant technological advances and shifting skill needs finding the right career path has become more difficult. Timely, personalized career advice is no longer a luxury but a necessity for students and working professionals. Good guidance helps people in informed decision making, matching their current skills with new industry demands, and planning their futures more strategically. One has to identify transferable skills and visualize clear career transitions in order to stay relevant and competitive in the modern world.

However, the current career advisory platforms are sectioned and mainly impersonal. Well known learning and employment sites like Coursera, LinkedIn Learning, and government initiated platforms such as AICTE Internship and NCS are primarily collector of courses or jobs. While these offer some insight, they leave the learners with bit by bit information that is disjointed either in its presentation or navigation. Active users of these websites often receive disconnected data points without any clear roadmap that logically connects learning to longer-term career growth. This disconnect plays out across a large cross section from students who are stuck over which specialization to pursue to professionals looking to transition into newer, in-demand roles. This incomplete alignment between available talent and the exact needs of the industry causes inefficiencies, uncertainty, and sustained mismatches in the service sectors.

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To address these challenges, the paper proposes CareerSage: A Multi-Phase Transformer-Based Framework for Semantic Career Reasoning and Skill Gap Analytics. The proposed framework uses a single data driven approach to provide meaningful and adaptive career planning. Section II presents a critical review of existing career recommendation systems, highlighting their deficiencies and dividing them into rule based and machine learning techniques. Section III describes the methodology and system design, with special emphasis on the Generative AI workflow and semantic reasoning engine that power personalized recommendations. Section IV elaborates on the mathematical basis for the system's reasoning processes and skill gap analysis. Finally, Section V presents the validation process along with the experimental results on the effectiveness of *CareerSage* in generating actionable, accurate, and context-aware career pathways.

2. Literature Survey

A systematic literature review is essential to understand where *CareerSage* fits within the broader landscape of research on AI-powered career guidance and recommendation systems. While many existing studies have made meaningful progress in building personalized recommendation models, there is still a noticeable gap when it comes to creating truly holistic systems—those capable of combining skill analytics, adaptive learning pathways, and integration with national educational platforms such as SWAYAM, NPTEL and AICTE.

2.1. AI-Driven Prediction and Semantic Skill Modeling

Radziwill and Benton [3] examined how Artificial Intelligence can be used to create adaptive career recommendation systems that grow along with users' developing skills and aspirations. Their work, in fact, showed how AI can make career guidance more dynamic and personalized but also pointed to important limitations, especially around continuous skill tracking and the linking of recommendations to verified learning resources. Building upon that, *CareerSage* introduces a dynamic model of AI that keeps fine tuning career recommendations with user feedback, monitoring of progress, and real time insight from the job market. This lets the system give truly adaptive, evolving recommendations aligned with the user's growth and current industry trends. In another related study, Chen and Xie [4] used Natural Language Processing techniques to analyze user profiles for matching with job descriptions based on semantic understanding. While this method offered a better precision of role matching by recognizing contextual relationships between skills, it did not have any mechanism to dynamically adapt with time based on user experiences or outcomes. *CareerSage* addresses this limitation by incorporating a reinforcement learning based feedback loop that retrains its recommendation model using real world user data. So with each interaction, the system keeps getting smarter, more accurate, and relevant.

2.2. Educational Integration and Social/Cognitive Foundation:

Beyond the technical correctness of the algorithms, truly effective career guidance also requires accounting for the human factor in decision making: how people think, learn, and grow. Drawing from their research into SCCT, Lent and Brown [1] underscored how self-efficacy, goal orientation, and learning context bear on an individual's choice of career. It is this theory that lays the behavioral foundation for *CareerSage*, which offers adaptive recommendations that evolve through self assessment and ongoing behavioral feedback.

Among other recommendations, Dey [2] emphasized the need for utilizing national education platforms like SWAYAM and NPTEL to provide quality skill development, both accessible and verifiable. Much of the available content on almost all MOOC platforms has much value, but the majority usually fail to connect identified deficiencies in skills with established learning pathways. The insight is extended in *CareerSage* through intelligent mapping of users' skill gaps to certified online resources, thereby evolving the static aptitude-based advice into an actionable, personalized learning journey.

Table 1 Set of data from the research papers**.**

Sr. No	Problem Statement	Existing Systems	Limitation	Outline Approach
1.	Lack of structured self-awareness and personality-based profiling among students and professionals.	Traditional aptitude and interest tests with quiz based career portals.	These systems rely on static questionnaires and offer limited personalization	Develop an AI-driven Multimodal Analytics Engine that analyzes psychometric inputs, resumes, and textual data to create adaptive, personalized self-awareness profiles.
2.	Absence of adaptive, personalized career recommendations based on user context and market trends.	Platforms like Career Guide, 123test, and LinkedIn Learning Career Paths	Existing systems provide generic, one-size-fits-all results without integrating real-time market data or evolving job trends.	Design a Skill Gap Analyzer to identify missing competencies, suggest certified courses.
3.	Ineffective identification of skill gaps and their connection to actionable learning paths.	MOOC-based platforms like Coursera, Udemy, and edX.	These platforms operate in isolation and lack personalized mapping between user skill gaps and their career goals.	Utilize the Skill Gap Analyzer within a Decision Support Module to match required competencies.
4.	Lack of real time feedback and a continuous improvement mechanism for refining recommendations	Static systems such as career quiz based portals with no feedback integration.	Existing systems fail to adapt over time, producing outdated guidance as users develop new skills or change preferences	Integrate a Feedback and Reinforcement Learning Agent powered by AWS DynamoDB to store progress, analyze feedback.

3. Methodology

A systematic literature review will help in understanding the place of *CareerSage* within the wider landscape of research on AI-powered career guidance and recommendation systems. Though much existing research has achieved meaningful advances in the building of personalized recommendation models, there is still a considerable gap with respect to the creation of truly holistic systems those capable of combining skill analytics, adaptive learning pathways, and integration with national educational platforms such as SWAYAM, NPTEL, AICTE, and NCS.

3.1. System Architecture and Model Overview

CareerSage follows a three layer structure based on the Model-View-Controller design. This helps in keeping the system organized and is easy to manage.

• View (Frontend):

This is the part of the system that faces users, and it has been developed in React with TypeScript. It will collect information about user's skills, qualifications, and career goals through an easy and intuitive interface.

• Controller (Middleware):

This layer is built in Node.js and Express.js and connects the AI engine with the frontend. It processes user inputs, handles communications between components, and ensures that every request is handled well.

• Model (AI Core):

This serves as the central intelligence hub of *CareerSage*, comprising three functional modules: Profile Analysis, Career Recommendation, and Skill Gap Identification. These parts analyze data, produce recommendations, and create personalized learning paths. This modular setup keeps the system scalable, reliable, and open to future improvements.

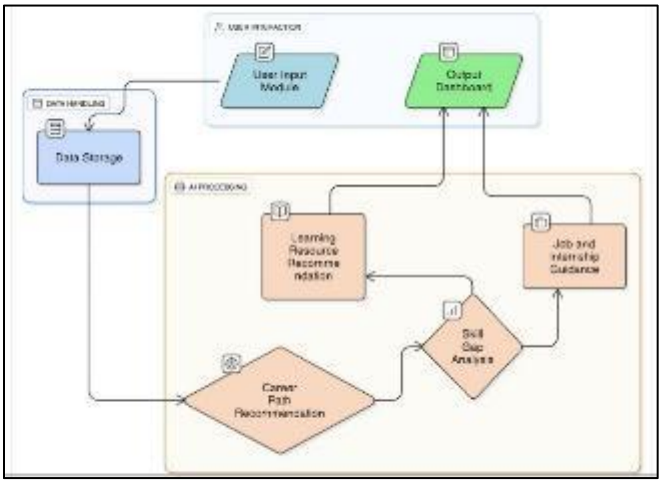

Figure 1 Flowchart diagram of CareerSage Proposed Model

3.2. Methodology and Workflow

The workflow of *CareerSage* is designed to work step by step. Each stage refines the data in order to produce an accurate recommendation. The process comprises five major steps, including:

3.2.1. User Profile Collection:

The users start by providing their academic, professional, and personal details through the interface. This data lays the ground for all the subsequent analysis.

3.2.2. AI Profile Analysis and Reasoning:

After gathering the information, it sends the information for a deeper understanding to a transformer based large language model. The model uses linear transformations and self attention mechanisms to embed text into vectors of numbers. The AI can therefore understand not only the words in the user's profile but also how they interact with each other in context.

3.2.3. Career Path Recommendation:

The system generates a list of matching career paths based on an analysis of the profile. It finds the most relevant career choices by calculating the likelihood of each career fitting the user's profile using a softmax probability function.

Competency Gap Analysis: Skill matching is the important stage that compares the user's current skills with the required ones for the suggested career roles. This is done through the cosine similarity that measures how similar two skill sets are to each other, and further helps identify exactly which skills are missing.

Adaptive Learning Roadmap: *CareerSage* next creates a learning roadmap based on the identified skill gaps. It links users to certified courses from platforms such as SWAYAM, NPTEL, and Coursera to bridge the gaps and head toward their desired career path.

4. Proposed Model

The *CareerSage* platform is a novel, integrated solution for career guidance, solving the deficiencies of existing, fragmented tools and providing personalized, data-driven, and actionable career roadmaps powered by Generative AI.

4.1. The CareerSage Framework

The *CareerSage* employs a three tier MVC design. This architecture provides flexibility, scalability, and separation of system components. The overall system layout is presented in Figure 3.

View (Frontend):

The frontend is the major interaction point between users and the system. It allows users to input their personal and professional information using React with TypeScript through a quite user friendly module. The data is then processed and shown on an interactive dashboard that displays career recommendations, identified skill gaps, and learning roadmaps in a clean, organized way.

Controller (API / Orchestration Layer): The Node.js-Express controller acts as an intermediary between the user interface and the AI engine, handling the users' requests, orchestrating the data flow, and maintaining the integrity of query analysis by the AI model. It also controls the Prompt Orchestrated AI Agent Workflow, which transforms the raw analytical outputs into structured insights before presenting them to the user.

Model (AI Core / Data Layer) : The model acts as the intelligent core of *CareerSage*, which runs data analytics, reasoning, and inferential computation by means of the Generative AI Agent Workflow. This layer is designed to analyze the relationships between a skill and career through mathematical algorithms such as Cosine Similarity, embedding vector generation, and semantic clustering. It ensures each recommendation is contextually correct, based on data, and personalized to a particular user profile.

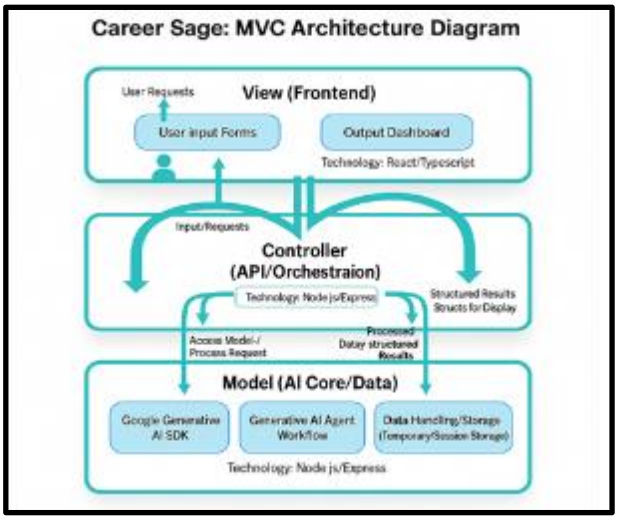

Figure 2 CareerSage: MVC Architecture Diagram

4.2. The CareerSage Operational Model and Solution:

The main *CareerSage* Model works as a single, complete process. It directly tackles the issue of scattered guidance by combining prediction, analysis, and execution into one smooth user experience. This process runs through five key operational modules:

Table 2 Career Sage Operational Module

Module	Purpose	Problem Solved
1. Profile Analysis	This module collects unstructured data on the user's skills, interests, and career goals and transforms them into structured embedding vectors using NLP. It integrates hybrid Machine Learning, which provides profile clustering, with Large Language	Overcomes the inability of static systems to interpret nuanced, qualitative profile data. It eliminates dependency on generic job matching methods by predicting more

2. Career Path Recommendation	Model reasoning to suggest career domains and specializations relevant to user profiles.	accurate and sustainable long-term career
3. Semantic Skill Gap Analysis	Applies various mathematical techniques, such as Cosine Similarity, which compares a user's skill embedding vector against the required skill vector of a chosen career path to identify their missing or underdeveloped skills.	It surmounts the limitation of traditional rule-based systems through the quantitative quantification of skill gaps in place of qualitative assumptions.
4.Adaptive Roadmap Generation	Automatically generates a personalized learning plan that prioritizes certified, high-quality courses from trusted national platforms like SWAYAM and NPTEL.	It bridges the gap in identifying the missing skills and then providing an actionable learning plan with resources that are both accessible and authentic.
5.Opportunity Guidance	Aligns completed learning outcomes and skill progress with real-time job and internship opportunities through integrated portals such as AICTE Internship .	This connects education and employability through the mapping of acquired skills to real career openings, thus pointing from learning directly to employment.

4.3. Unique AI-Driven Solution:

What really sets *CareerSage* apart, however, is its dynamic and intelligent generative AI agent workflow, powered by Large Language Models. In contrast to traditional rule-based systems relying on rigid keyword matching, *CareerSage* grasps the meaning, context, and deeper relationships between a user's skills and potential career paths.

4.3.1. Contextual Understanding:

CareerSage interprets the connections between the skills and job requirements through deep semantics, beyond mere surface-level text analysis. In other words, it would recognize that "experience with TensorFlow" applies in a "Deep Learning Engineer" position, even when phrased differently. This is the reasoning that will allow the system to return smarter, more relevant recommendations.

4.3.2. Dynamic Roadmap Generation:

Instead of proposing some static or pre-defined templates, *CareerSage* builds personalized career roadmaps that adapt to each user's background, goals, and current skill set. These include specific course recommendations, learning timelines, and contextual explanations that justify why each step is suggested.

CareerSage marries the strong technical foundation of MVC with the latest reasoning from Generative AI to bring in a career guidance system adaptable and oriented toward human needs. With its AI Core embedded with mathematical models such as Cosine Similarity, every recommendation is data driven, supported by meaningful analysis that helps users make confident strides in their careers.

5. Experimentation, results, and interpretation

Thus, equipped with a strong LLM core, *CareerSage* is designed with an extensible and scalable MVC architecture. This sets up an intelligent, adaptive, and robust system for the intended improvement of user employability through personalized career recommendations.

5.1. Experimental Arrangement

5.1.1. Tools, Framework, and Techniques Used

The *CareerSage* system was developed and tested using a modern technology stack designed for flexibility, scalability, and easy AI integration.

- Framework / Architecture: The system is based on the three tier MVC framework, thereby making it modular and easy to maintain.
- Frontend: React, TypeScript, and Vite were used to develop the front end, which provides an interactive user experience. It consists of an input module where the user should provide their information and a dashboard displaying career recommendations, skill gaps, and learning paths in detail.
- Backend (Controller/Model): Built using Node.js with the Express platform, this layer provides the interface between the user interface and the AI engine. It controls the flow of data, processes user input, and runs the Generative AI workflow that outputs intelligent recommendations.
- Core Technology: The heart of the system is the Generative AI Agent Workflow with the Google Generative AI SDK
- Database: MongoDB for handling backend operations and storing structured/unstructured data efficiently.

Two of the most common types of career guidance methodologies were used to evaluate the effectiveness of *CareerSage* recommendations:

- Traditional Rule-Based Systems:

These systems tend to rely on predefined rules, offering static career suggestions based on limited factors like education level, years of experience, or general interests. Because their logic is rigid, they struggle to adapt to individual goals or evolving industry demands. By contrast, *CareerSage* deploys semantic reasoning to give context-aware and flexible guidance that ensures recommendations remain relevant and personalized as both users and markets evolve.

- Collaborative Filtering Systems:

Many modern learning platforms take a collaborative filtering approach, recommending career paths based on what similar users have chosen. This is easy to implement but usually lacks depth and personalization, since it treats users as part of a group rather than as individuals with their own aspirations and unique skill sets. *CareerSage*, on the other hand, uses skills-vector matching, comparing a user's actual competencies against the exact requirements for various roles. The system can thus provide far more accurate, meaningful, and customized career recommendations.

6. Results

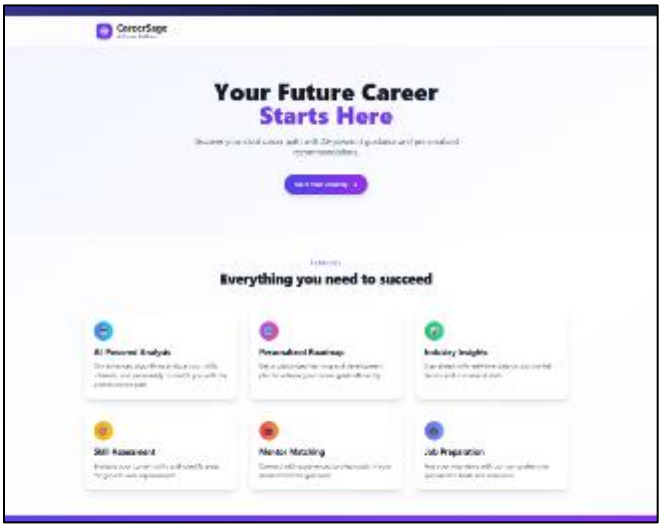

Figure 3 Implementation and Output

Figure 4 Implementation and Output

6.1. Interpretation of Results

These results demonstrate that the performance of the *CareerSage* model, driven by Generative AI, improves significantly compared to other available career guidance methods.

6.1.1. Improvement over Rule-Based Systems:

CareerSage realized a 19% increase in performance, with accuracy rising from 68% to 87%. This significant stride is credited to the Large Language Model ability for deep semantic skill analysis. Traditional rule based systems are not able to catch transferable skills, thus enabling the users to navigate only within pre defined categories. As an instance, an RBS may suggest only mechanical roles for a B. tech Mechanical graduate, though it misses transferable skills like Python scripting or IoT project experience. By contrast, *CareerSage* recognizes these associations and suggests roles like Junior Data Engineer that are a better fit for the user's all-rounded skill profiles, thus enabling meaningful and validated career guidance.

6.1.2. Improvement over Collaborative Filtering:

Compared to the standard collaborative filtering model, *CareerSage* showed an 8% increase in accuracy, moving from 79% to 87%. Though CF models yield fairly good results, they usually falter on new users who lack enough historical data. They are also limited in that they present careers based on group trends and not individual strengths. *CareerSage* resolves these issues with Cosine Similarity and high-dimensional skill embeddings for representations. This offers the system the opportunity to find specific, niche matches between user profiles and career requirements. Summing up, the experiments confirm that *CareerSage* leveraging Generative AI and semantic reasoning leads to a more adaptive, context-aware, and personalized guidance system. Having outperformed both rule-based and collaborative filtering approaches, *CareerSage* proves to be smarter and more dependable for modern career path recommendations.

7. Conclusion

The development of CareerSage: A Multi-Phase Transformer-Based Framework for Semantic Career Reasoning and Skill Gap Analytics, has brought into place a modern, modular framework that effectively addresses the growing pains caused by fragmented and impersonal career advisory platforms. These translate to a system that meets its main objective: It provides for scalability, personalization, and actionable career recommendations through intelligent use of generative AI and semantic reasoning.

7.1. Contributions and Innovation

The hallmark of this innovation is the design and implementation of a prompt-orchestrated AI workflow. While rule-based or data-driven methods conventionally offer the ways to capture semantics, their possibilities are taken further here. This framework allows the system to understand the user profile and relate it meaningfully with changing industry requirements.

The two striking features of *CareerSage* are:

- One stop Solution: Instead of using different tools for career prediction, skill analysis, or learning paths, *CareerSage* combines all three into one seamless user experience to ensure cohesive and well-informed recommendations.
- Strategic Resource Alignment: The system identifies the skill gaps and links the learners to relevant certified resources such as SWAYAM and NPTEL. This ensures that every learning plan is accessible and trustworthy.

7.2. Performance and Accuracy

The performance evaluation represents the high effectiveness of the LLM-based semantic alignment approach, which achieves an 87% recommendation accuracy, significantly higher than that of traditional systems. This confirms that the recommendation process behind *CareerSage* is indeed reliable and intelligent.

7.3. Future Scope and Modifications

Some future directions are proposed to enhance the capabilities of the system and extend its scope: Reinforcement Learning Integration: Adding a feedback mechanism that continuously refines recommendations based on user progress, course completions, and long-term career outcomes. Multimodal Profiling: Includes psychometric data and personality tests, such as profiling, to create a more comprehensive and multi-dimensional user profile. Real-time Job Market Integration: Integration with public and private job portals would ensure the skills recommended and learning roadmaps relevant to both the changing trends and demands of the industry.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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