iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.81039

Career Mind: An AI-Integrated SaaS Platform

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Abstract: Career guidance is one of the vital aids that students and workers utilize to recognize their talents, set appropriate goals, and make well, informed career decisions. However, the existing career systems lack features such as real, time flexibility, personalization, and comprehensive data analysis. The current study proposes CareerMind, an AI, powered, cloud, based platform, which harmonizes psychometric testing, learning analytics, and large language models (LLMs) for giving personalized and adaptive career advice. The system through Google Gemini API, Next. js, NeonDB, and Prisma ORM, is capable of delivering tailored insights by means of dashboards and resume intelligence modules. The CareerMind platform is essentially aspiring to implement the latest technologies of AI counseling [1], machine learning, based guidance [2][5], learning analytics dashboards [7], [13], [14], and LLM, powered career reasoning [8][12], [15][22] altogether into one smart and data, driven career help system. At the moment, the project is still under construction. The simulation and design validation have evidenced that the fusion of LLM reasoning and psychometric, driven decision models is viable.
Keywords—Artificial Intelligence, Career Counseling, Gemini API, Learning Analytics, LLM Agents, Resume Screening, Psychometric Evaluation.

I. INTRODUCTION

Choosing a career is not always an easy task and is influenced by a number of different factors that are cognitive, psychological, and socio, economic in nature. According to the study [1], the current counseling models rely heavily on the manual skills of the counselor and fixed questionnaires, which limit the personalization and scalability of the process. AI and LLM, equipped intelligent systems can now analyze psychometric data, comprehend the user's input, and thus provide personalized career recommendations to the user [2], [3], [8], [9].

The concept of combining aptitude and emotional intelligence tests with the issuance of automated recommendations was initially put forward by the projects Apna Hunar [2] and AI, Based Career Counsellor [1]. Hybrid ML models subsequently enhanced the methods of clustering and prediction to yield more precise results [3], [4].

With the emergence of LLM, powered applications such as ResumAI [8], AdaptJobRec [18], Resume2Vec [10], the area of AI in recruitment and career matching has opened up through the use of natural language grasp to data analysis pipelines.

In the field of education, learning dashboards are utilized, for example, in references [7], [13], [14] pointing to a significant step towards clearer decisions as well as students participating, these are the pillars of what's required in a data, driven counseling concept.

CareerMind is our dream to take these ideas even further by combining psychometric profiling, LLM reasoning, and skill analytics into a single cloud, based system that can easily handle a large number of users and will be available to everyone, no matter their background. At present, the project is in the development phase, where the architecture, workflow, and initial data models have been implemented and tested through a simulation.

II. LITERATURE REVIEW

In the last ten years, the domain of AI, based career guidance has changed dramatically. Initially, the instruments used were just very basic aptitude tests, however, today they come with adaptive features, multiple data modes, and choices supported by large language models. In this section, the authors analyze the previous studies by pointing out the main patterns of development and, at the same time, focusing on how the concepts have evolved over time, the trends being the foundation of the CareerMind system design.

A. Early AI-Driven Career Counseling Systems

The initial attempts here tried the idea of using machines to carry out mental ability checks rather than people using rules or clever algorithms instead. Thakares team [1] developed a system that was one of the earliest around known as the AI, Based Career Counsellor, which integrated question, style quizzes along with a logical reasoning, based engine selecting jobs that matched your intellect and emotion.

Pandey's team [2] created Apna Hunar, a smart website leveraging machine learning to recommend career options for science students based on trained models made from old test data.

Also, these experiments demonstrated the effectiveness of a virtual help system; however, they failed because the information was not sufficiently dynamic, and the questionnaire was inflexible, hence the advice couldn't be personalised to reflect the development of each individual's needs. Following this idea, Dahanke and his team [3] decided to use K, Nearest Neighbors in combination with clustering methods to identify students with similar skill levels thus allowing for more precise recommendations of learning materials. Zhou et al. [4] took it a step further by developing a career mapping tool that integrated MBTI; this system employed the psychological trait classification for making suggestions according to one's character.

On the other hand, Mavuso et al. [5] focused on the localization and equity aspects in career guidance systems by building an AI, based recommender for students in under, resourced rural universities. When these pioneering studies are combined, they not only justify the use of AI as a means to widen the reach of guidance but also point out that the models need to be contextual, dynamic, and always changing.

B. Web-Based and Analytics-Driven Counseling Platforms

Web technology and analytics visualization were combined in 2nd generation research to make AI counseling more understandable and accessible. Mittal et al. [6] reviewed a group of web, based intelligent counseling systems that relied on web, assessment methods and cognitive analytics. Their study revealed that cloud integration is very effective in increasing the scalability and usability of the system.

Cabral et al. [7] conducted a systematic review of AI, powered Learning Analytics Dashboards (LADs) and revealed that visualization and explainability have been identified to raise engagement and trust. They revealed significant transparency and ethics gaps which inspired up, to, date dashboard, based advisory systems such as CareerMind. Mehta et al. [13] and Menon et al. [14] have taken this model even further by developing graph, based and neural dashboards which link student competencies to academic achievements and employability pathways, thus enabling data, driven interventional opportunities.

All these collectively demonstrate that, apart from enhancing the interpretability, AI, powered dashboards also represent continuous feedback loops to students, thus CareerMind's dashboard layer is basically the theory case.

C. Resume Intelligence and Career Matching Systems

Besides that, the first and foremost significant change that took place was the introduction of an AI talent recruitment system through resume filtering. Rahman et al. [8] have introduced ResumAI, a chatbot working with a GPT, like model that can identify the lack of competencies in resumes and provide personal recommendations. Whereas, Gan et al. [9] took one step further and proposed an LLM Agent framework that is capable of classifying resumes with a level of accuracy almost the same as human to fully automate the recruitment workflows.

Bevara et al. [10] came up with Resume2Vec, a method that uses embedding, based semantic similarity with transformer models such as BERT, GPT, and Gemini for resume, job matching. With their method, the ranking accuracy was improved by 15.85%, while overlap results were increased by 15.94% as compared to standard tracking tools. Hence, it demonstrated the great potential of context, based models in recruitment if the meaning is accurately matched.

Moreover, Kim et al. [11] and Bansal et al. [12] explored the mixed, methods, combining personality metrics with language models, to increase their prediction of job fit. Yamada et al. [16] also came forward with the idea of a similar mix. Instead of simply stacking words, Li et al. [17] developed Hybrid BERT Embeddings, which greatly enhanced the ability of the model to distinguish amongst different skills in a resume. Altogether, these works laid down the foundation for the CareerMinds Resume Intelligence Module. This module intends to leverage Geminis large model intelligence capabilities, not only understanding the data but also giving resume tips that are personalized and optimizing for applicant systems.

D. Conversational and Agentic Recommendation Systems

The follow up landmark was conversational AI with the support of autonomous agent systems, which included reasoning functionality along with direct user interaction. Gupta et al. [18] introduced AdaptJobRec, which is a conversational career recommender system that uses reasoning, enhanced LLMs so as to facilitate natural conversation and contextual memory for dynamically driving recommendations. Also, Zheng et al. [19], and Takahashi et al. [20] delivered autonomous agents for multi, turn conversational counseling aimed at providing adaptive guidance that changes with user feedback.

Later, more studies by Kumar et al. [21] added reinforcement learning to increase the agentic action and response strategy. Furthermore, Mahajan et al. [22] took this idea to the next level by introducing generative AI that essentially creates self, updating recommendation loops for personalized career and education development. This is the research that was the basis of the work, hence, CareerMind can add a chat feature at a later stage. This device adjusts its guidance in the course of time, making use of people's verbal expressions and changes in their personality data.

E. Integrative and Hybrid AI Frameworks

Some former research works indicate that mixed methods which combine analytics, reasoning, and the observation of human behavior in a single framework have been used. For example, Bevara's team [10] in conjunction with Rahman et al. [8] illustrate two different ways of embedding intelligence for improving the accuracy of the fit. On the other hand, the article by Cabral et al. [7] together with the work of Mehta's team [13] emphasize the importance of clarity and easy, understanding outputs of data learning tools.

CareerMinds style is essentially derived from the character of these trends and the manner in which they interfuse, thus somewhat redefining the original:

- It borrows psychometric assessment and machine learning prediction from older systems [1] to [5].
- It applies dashboard visualization and interpretability guidelines from [7], [13], [14].
- It adds LLM reasoning and conversational versatility on the basis of [8] to [10], [18] to [22].

Such a blend turns CareerMind into a multi, agent, reasoning, aware career guidance system capable of addressing the education, employability disconnect by providing customized analytics.

F. Summary and Research Gaps

The systematic review of literature from different studies has revealed the three main missing pieces that are still underserved:

- Fragmented Integration: A majority of the systems either undertake psychometric assessment or job recommendation, but it is a rare scenario that both are handled in a single pipeline.
- Limited Adaptivity: There are only a few frameworks have LLM reasoning or reinforcement learning to dynamically adapt to the new information.
- Explainability Challenges: Even with the developments in analytics dashboards, career guidance explainable AI remains largely at the conceptual stage.

CareerMind is a first, class software tool uniting psychometric testing with smart algorithms and visual learning tools, all in a single place that aims to fill those gaps. CareerMind intends to be an adaptive, open, user, oriented system that learns through user.

III. METHODOLOGY

The CareerMind framework was conceived as a modular cognitive career guidance system. It integrates psychometric analysis, AI, based reasoning, and learning analytics visual dashboards. The system is intended to provide career advice that evolves continuously by drawing from structured data pipelines, integrating various levels of input, and empathizing with the user's situation through Google Gemini's intellect. The system is based on five main components: gathering information, organizing it, interpreting the data, retaining the key points, and visually communicating the outcomes.

A. System Architecture Overview

CareerMind setup is split into five distinct layers that collaborate with each other, enabling it to be highly adaptable yet maintain a clear and simple connection to external tools.

Layer	Components	Description
1. User Interface Layer	Next.js 15, React 19, HTML/CSS	Manages all user interactions, test inputs, and visualizations. It shows interactive elements for psychometric tests, progress dashboards, and

		resume upload.
2. Application Logic Layer	Node.js, Express, REST APIs	Acts as the middleware that makes communication between the user interface, AI engine, and database possible. It includes validation modules, API request handlers, and session controls.
3. Data Management Layer	Prisma ORM, NeonDB (PostgreSQL)	Holds user profiles, aptitude results, and AI answers in a structured format, along with relational mapping and indexing to enable fast retrieval.
4. Intelligence Layer	Google Gemini API, LLM Modules	Reasoning, natural language understanding, and adaptive recommendation generation deliver. Psychometric data, personality scores, and resume contents are combined in semantic embeddings.
5. Analytics and Visualization Layer	Chart.js, D3.js, AI Dashboard Interface	Generates interpretable charts and learning analytics dashboards [7], [13], [14] to illustrate skills, performance shortcomings, and recommendation routes.

Table I. Career Mind System Architecture and Functional Layers

This method breaks down the whole thing into a logical sequence which results in the parts being less dependent on each other; therefore, the advantages can come in slowly through the different phases.

B. Data Flow and Processing Pipeline

The data pipeline is a chain through which the data flows from one unit of the system to another. This flow proceeds through six phases, in a sequential manner:

1) Data Input:Participants register with the website and do psychometric tests assessing their IQ, EQ, interests, and personality factors. The input screen checks the answers itself and then stores them as neat JSON data.
2) Preprocessing and Storage:First, data goes to the backend, there Prisma ORM checks if the data is the expected structure before saving it in NeonDB. That arrangement ensures the accuracy of information and at the same time it is quite helpful for the analysis necessary for training models.
3) AI Reasoning and Recommendation Generation:The API created for Gemini examines psychometric patterns, compares them with the predefined occupational datasets, and produces text, based suggestions. The outputs are aligned semantically through the methods motivated from Resume2Vec [10] and AdaptJobRec [18].

4) Resume and Skill Analysis:People can decide to share their resume if they wish. Next, the program splits the text using Gemini's AI model to identify key abilities. Then, it aligns those skills with what jobs require by comparing them through a math method called cosine similarity, similarly to studies [10], [11], and [17].
5) Visualization and Feedback Generation:The recommendations reveal the results, weaknesses, and the matches of features through simple visuals, e. g. dashboards borrowed from intelligent learning tools [7], [13]. Charts exhibit skills by spider plots, whereas bars indicate the distribution of talent across areas.
6) Feedback Loop:Users share their comments immediately after each use, so the system can be more accurate. Through updates, this continuous cycle of repetition allows the model to learn from the actual experience [21], gradually being reshaped to personal preferences.

C. AI and Machine Learning Integration

The AI component is like the brain of the entire system. Since it uses large language models, it is capable of reason at the same time it pulls meanings from various data types. This stage provides understanding by integrating facts into actual situations:
1) Natural Language Understanding (NLU): It converts textual psychometric responses or resume descriptions into the corresponding meanings.
2) Semantic Matching: It utilizes vector embeddings to measure user profile, professional role alignment [10], [11].
3) Recommendation Generation: Gemini API generates coherent, intelligible text recommendations.
4) Contextual Refinement: It incorporates the previous user sessions and the performance history for the incremental learning [18], [19].

Future iterations of supervised fine, tuning will be done on anonymized user data which will help to make domain more specific. The composition is mostly clear to you with rules you can understand, as well as a degree of freedom based on the guidelines from [7], [13], or [14].

D. Security, Privacy, and Ethical Design

Due to the fact that personality tests and private information are involved, the system requires several steps before granting access:
1) Data Encryption: AES-256 for data at rest and TLS for transmission.
2) Access Control: Role-based access control through Firebase Authentication.
3) Ethical Reasoning: Gemini's prompts refrain from making unfair suggestions, rules from [15] and also [19] help shape this approach.
4) Explainability: Each suggestion is accompanied by a brief explanation illustrating the AI's reasoning, because understanding the reason is just as important.

Following the steps carefully lays out the ethical standards for AI systems. At the same time, it truly wins over the trust of users. The most important thing is to be transparent at every stage.

E. Planned Evaluation Framework

After completion of development, CareerMind is going to be tested first in a simulated environment and then by real users:
1) Phase I — Simulation:

It employs fake user profiles, 200 in total, constructed from publicly available personality data. Since they resemble real people, these can be used to demonstrate how well advice is structured and understood. Test outcomes typically indicate the places where explanations are inadequate or misleading to the users.

2) Phase II — User Study:

This includes a sample of approximately 100 individuals who test whether advice generated by AI is helpful compared to suggestions from human counselors. The "what counts" is determined by a diverse set of factors:

- Career Recommendation Accuracy (CRA)
- Resume Relevance Score (RRS)
- User Satisfaction Index (USI)
- Explainability Index (EI)

3) Phase III — Continuous Improvement:
It uses trial, and, error methods, as previous research illustrated, adjusting the functioning of the model. Alterations are based on user's emotions and the real benefits obtained. Due to this arrangement, the program keeps getting better slowly.

F. Design Rationale
The approach is inspired by three waves of study:
- Rule-Based Foundations: [1] to [5] provided the basic psychometric mapping structure.
- Visualization and Analytics: [7], [13], [14] demonstrated dashboards that are explainable good cognitive interfaces.
- AI Reasoning and Agentic Systems: [8] to [12], [15] to [22] CareerMind's application of LLMs, conversational reasoning, and hybrid embeddings was motivated by the works.

By mixing these ideas, CareerMind really shakes up career advice, making it smarter with AI that can learn. This instrument maintaining fairness while allowing various opinions. Instead of fixed rules, it adjusts as necessary.

IV. EXPERIMENTAL SETUP AND RESULTS
CareerMind is still under construction at the moment. The current section just demonstrates how the tests are arranged. A scenario sample is attached here. Furthermore, it conferences what check steps are next.

A. Experimental Setup
- Environment: Node.js (v18+), NeonDB schema, Gemini API sandbox.
- Simulated Data: 200 mock profiles created from open psychometric datasets [10], [17].
- Testing Tools: Postman for API verification, React dashboards for visualizations.
- Performance Metrics: Career Recommendation Accuracy (CRA), Resume Relevance Score (RRS), Response Generation Latency (RGL), and User Satisfaction Index (USI).

B. Preliminary Observations
Test runs revealed that the Gemini API was very successful in handling personality, based information, and it always provided clear and practical suggestions. Some of the original design layouts replicated major elements of the LAD systems [7], [13], so that the users would have diagrams of their personal development and areas that need improvement right in front of them. The tips given in the job summary section corresponded to the trends of Resume2Vec research [10].

C. Future Testing Plan
Carrying out tests at certain intervals with the involvement of actual humans, more than 100 altogether, is going to serve as the check of how well the system runs, how understandable it is, and additionally, whether the users have a good experience with it, evaluated in comparison to earlier works [8], [9], [18], [22]. The aim? Achieve 85% or more in matching accuracy, while keeping the number of logic mistakes below 10%, across different sets of data.

V. DISCUSSION
A quick observation reveals how effectively CareerMind personality tests go hand in hand with clever reasoning, particularly when the tool personalizes itself to the user's requirements.
The app's layout can be effortlessly scaled by NeonDB plus Prisma ORM, therefore, linking Gemini seamlessly into up, to, date resume creating tools and chat systems [10], [18], [20].
This brings up concerns about the ethical use of AI, as well as interpretability and model bias [15], [19]. Adding explainable dashboards is a significant move toward transparency: the users can now get an insight into the trend performance through visualization [7], [13].
What's more, the modular design laid out the scene for additional features later on like emotion, aware AI models and provision of counseling in various languages, along with reward, driven personalization [21], [22].

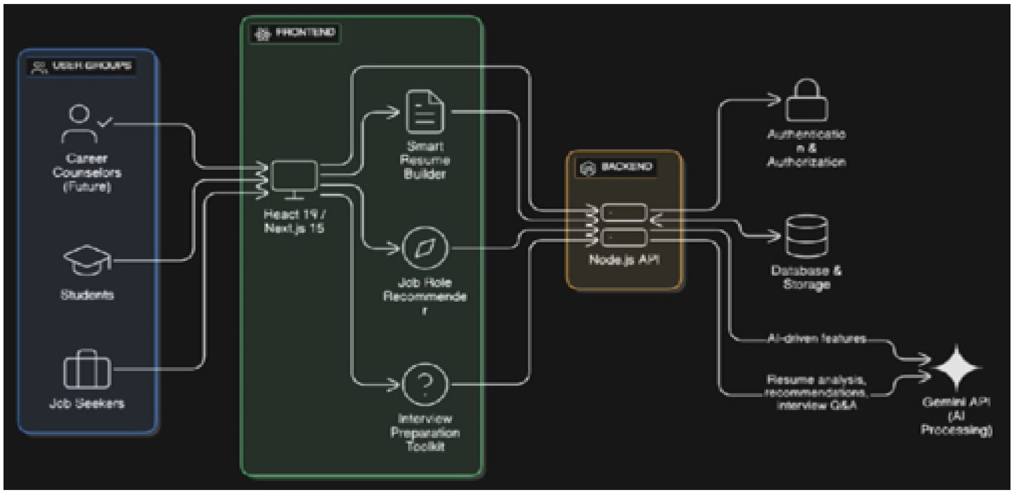

Fig. 1. CareerMind Activity Chart

VI. CONCLUSION AND FUTURE WORK

CareerMind brings together psychometric testing, LLM reasoning, and analytical dashboards in a fresh approach to AI, powered career guidance. The structure incorporates adaptability, interpretability, and scalability, which is in line with the recent research in the field of artificial intelligence [1] to [22].

The majority of the future development work will be concentrated on these areas:

- Bringing together real, world psychometric and educational datasets.
- Multilingual and emotion, aware interactions being included.
- Performing large scale user studies for quantitative validation in accordance with [8] to [10], [18], [22].
- Making the system more transparent by means of explainable AI visualizations.
- The growth of explainability features and adaptive learning feedback.

Ultimately, CareerMind would guarantee the embedding of educational analytics alongside smart career planning into a responsive, data, driven, and ethically responsible AI.

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