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AI-Driven Career Guidance for Graduates

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Abstract*— Choosing an appropriate career path has become increasingly complex for today's graduates due to the vast number of options and growing competition across industries. Many individuals struggle to identify a career that aligns with both their academic strengths and personal attributes. Traditional career counseling methods often rely on standardized tests or general academic performance, failing to provide the personalization needed for meaningful career decisions. This paper introduces an AI-driven career guidance system designed to offer customized recommendations by analyzing both academic background and individual personality traits. The proposed approach takes into account behavioral tendencies, interests, and subject knowledge to suggest career paths that better reflect a student's overall potential. Unlike conventional methods, the system adapts over time by incorporating feedback and staying aligned with evolving job market trends. It aims to assist students, educators, and counselors by providing a more holistic, data-informed framework for career planning. By bridging the gap between personal traits and professional requirements, this model enhances decision-making and helps reduce career mismatches. Future extensions could include integration with real-time labor market analytics and natural language processing tools to further increase system relevance and accessibility.

***Index Terms*—Career Guidance, Artificial Intelligences, Academic Profiling, Machine Learning, Career Recommendation System**

I. Introduction

In an era marked by rapid technological advancement and diversification of job roles, selecting a suitable career path has become a complex and often overwhelming task for recent graduates. Although many students complete their formal education with strong academic records, they frequently encounter difficulties in determining a professional trajectory that aligns with their skills, values, and long-term goals. The lack of personalized career guidance contributes to confusion, indecision, and, in many cases, long-term dissatisfaction in the workforce [1], [2].

Traditional career counseling methods—such as standardized aptitude tests, generic career suggestion portals, or one-on-one sessions with advisors—are often limited in their scope and effectiveness. These approaches typically focus on academic qualifications or predefined aptitude metrics while neglecting important aspects of an individual's personality, behavioral traits, and emotional inclinations [7], [10]. As a result, students may receive recommendations that do not reflect their true interests or working style, ultimately leading to poor job satisfaction, misalignment with organizational culture, or frequent career switching.

Moreover, the scalability of traditional guidance systems remains a challenge, especially within institutions managing large and diverse student bodies. The need for continuous updates based on evolving industry demands further complicates the applicability of conventional models. The dynamic nature of today's labor market—driven by automation, digital transformation, and global competition—requires more adaptive and intelligent career support tools.

With the rise of Artificial Intelligence (AI) and Machine Learning (ML), there is now a significant opportunity to transform career counseling into a data-driven, personalized, and scalable process. AI-based systems have demonstrated strong capabilities in analyzing large datasets, identifying patterns, and making predictive decisions in fields such as healthcare, finance, and education. When applied to career guidance, AI can help bridge the gap between student potential and professional opportunities by incorporating a wide range of inputs, including academic records, domain expertise, psychometric factors, and evolving market trends [4], [5], [9].

One particularly promising element in this evolution is the use of psychometric profiling, such as the Big Five Personality Traits model, which evaluates dimensions like openness, conscientiousness, extraversion, agreeableness, and emotional stability. These traits have been proven to play a key role in predicting job performance, satisfaction, and workplace compatibility [4]. By integrating such behavioral assessments with technical evaluations, AI-powered platforms can offer more accurate and meaningful career suggestions tailored to the individual [5], [6].

This research proposes a comprehensive AI-driven framework that combines technical proficiency testing with psychometric evaluation to provide personalized career recommendations. Unlike traditional models that are rigid or academically biased, the proposed system adapts over time through continuous user feedback, making it responsive to both individual preferences and market changes. It not only empowers students to make more informed decisions but also enhances the capacity of academic institutions to deliver effective career services at scale.

Key Contributions

The major contributions of this research are outlined as follows:

- Development of a hybrid AI-based career guidance model that integrates domain-specific assessments with personality-based profiling.
- Application of the Big Five Personality Traits model for behavioral analysis and alignment with career environments [4], [10].
- Implementation of supervised learning algorithms capable of generating adaptive and personalized career recommendations [2], [8].
- Comparative evaluation of the proposed framework against existing approaches to highlight its advantages in personalization, adaptability, and scalability [5], [7].

This work aims to assist students in making thoughtful and confident career choices, strengthen institutional guidance frameworks, and enable employers to identify individuals whose personal and professional profiles best match their organizational needs.

II. Related Work

Several AI-based career guidance platforms have been proposed in recent years, each leveraging different techniques ranging from rule-based logic to machine learning algorithms. Joshi et al. [1] introduced a questionnaire-based model to match users with careers based on predefined answers. While this method was user-friendly, it lacked personalization, offering static recommendations without considering user growth or personality. Similarly, Shivakumar et al. [2] developed a system using decision trees and random forests to predict career paths from academic data. Their results were promising in terms of classification accuracy, but the system did not account for psychological traits or long-term career satisfaction.

Vidyashreeram and Muthukumaravel [3] used classification techniques such as KNN and SVM to predict suitable careers based on students' academic performance. However, their approach lacked adaptability and did not offer feedback mechanisms to improve model learning over time. In contrast, Rao et al. [4] explored the use of neural networks and psychological assessments to generate career recommendations. This approach was more comprehensive but limited in domain coverage and did not integrate skill-based testing. Nair et al. [5] presented a chatbot that could suggest careers based on user interaction, though the underlying model was rule-based and static, lacking the flexibility of learning from user feedback.

Roy et al. [6] compared traditional classifiers such as Naive Bayes and KNN for career prediction. They concluded that while these models were computationally efficient, their predictive power was limited when used in isolation. Their research highlighted the need for multi-layered decision models. Mehraj and Baba [7] emphasized the importance of using explainable AI in career guidance tools. Their findings revealed that many current systems operate as black boxes, providing little transparency or reasoning behind recommendations—raising concerns about trust and ethical AI.

Sharma et al. [8] introduced a hybrid recommendation engine that combines content-based filtering with collaborative filtering, primarily aimed at job recommendations rather than student career guidance. While effective in dynamic environments, their model was less suited for early-career individuals who lack historical work data. Kaur and Kaur [10] presented a broad review of career guidance systems, identifying that most focus solely on academic scores. They advocated for systems that also consider user interests, personality types, and soft skills to provide a more balanced recommendation.

Other researchers have attempted to combine psychological and academic factors to improve accuracy. For instance, Singh and Gupta proposed a framework that includes emotional intelligence as a deciding factor for career prediction, showing improved user satisfaction. However, their model was constrained by a small dataset and lacked validation in real-world settings. Another notable approach by Thomas et al. explored goal alignment and self-perceived motivation, using semi-supervised learning to enhance decision-making. Yet, it was limited to students from technical backgrounds.

Moreover, existing systems often fail to address the changing dynamics of the job market. Many recommendation tools are trained on static datasets and do not incorporate emerging job roles or skill demands. This creates a gap between educational training and employability, especially in fast-evolving industries like AI, cybersecurity, and data science. Few models offer feedback mechanisms where user outcomes (such as satisfaction or success in the chosen path) help refine the recommendation process.

Additionally, most tools lack modularity, meaning updates or personalization are difficult to implement once the system is deployed. Scalability and domain adaptability are also overlooked, as many systems are designed for narrow academic streams or regional job profiles. Finally, explainability remains a challenge—many users do not understand why a specific career path was recommended to them, which affects trust and usability.

To overcome these issues, our proposed system offers a multi-layered architecture that combines psychometric evaluation, skill testing, and adaptive machine learning with explainable outputs. Unlike many existing models, it is designed to evolve based on user feedback, and can adapt to individual learning paths, interests, and personality traits. This holistic and user-centric approach aims to bridge the gap between student potential and real-world opportunities more effectively.

III. Literature Review

Artificial Intelligence (AI) has played an increasing role in career guidance systems in recent years. Various researchers have explored the use of machine learning and data-driven techniques to predict suitable careers for students based on multiple inputs such as academic performance, personality traits, and user preferences.

Joshi et al. [1] developed an AI-based online career counselling system that recommends careers using student performance data. Their approach uses decision-making logic to match user inputs with relevant job profiles. Similarly, Shivakumar et al. [2] proposed a career prediction model that uses machine learning algorithms to suggest career paths. The study found that classification algorithms like Decision Trees and Naive Bayes were effective in producing accurate predictions.

VidyaShreeram and Muthukumaravel [3] also used supervised learning approaches to predict career paths based on historical data. Their system emphasized the importance of training models with accurate and updated datasets. Rao et al. [4] went further by using artificial neural networks (ANN) for personality-based career prediction, demonstrating how personality traits can be valuable inputs when designing career recommendation systems.

Nair et al. [5] introduced an AI-powered chatbot for career counselling, which allows students to interact in real time and receive career suggestions based on their responses. The integration of Natural Language Processing (NLP) in such systems offers a more conversational and user-friendly experience.

Roy et al. [6] explored the use of advanced machine learning techniques including K-Nearest Neighbors and Support Vector Machines to improve the performance of student career prediction models. Mehraj and Baba [7] conducted a broader review of AI-driven career guidance platforms and highlighted the need for transparency and interpretability in these systems to build user trust.

A hybrid recommendation system for job matching was proposed by Sharma et al. [8], combining both content-based and collaborative filtering. Their method improved recommendation accuracy by leveraging both user preferences and item features. Similarly, Patel and Shah [9] designed an NLP-based system for matching resumes with job descriptions, showcasing how AI can also benefit the recruitment side of the career ecosystem.

Kaur and Kaur [10] provided a detailed review of AI techniques used in career guidance, emphasizing both the potential and the limitations of current technologies. Their findings stress the importance of adapting AI models to diverse student populations and ensuring fairness in recommendations. Overall, existing literature reveals promising advancements in AI-driven career guidance, yet there remain challenges in personalization, psychological evaluation, and ongoing adaptability of such systems.

IV. Methodology

The proposed system is a hybrid AI-powered career guidance platform that evaluates both technical competence and psychological attributes to recommend suitable career paths. It integrates psychometric assessment, domain-specific testing, and supervised machine learning models to deliver personalized, adaptive recommendations [2], [7], [10]. The system consists of five core components: a User Interface, Personality Analyzer, Skill Assessment Module, ML-based Predictor, and a Feedback Loop to enable continuous learning [5].

A. System Overview

An overview of the workflow is illustrated in Fig. 1. The process begins with users completing two assessments: a Big Five personality inventory and a domain-specific skills quiz. The Big Five framework is widely used in psychological profiling and has been applied in various AI-based career recommendation systems [7]. The responses are combined into a feature vector, which is analyzed to generate career suggestions using trained machine learning models [4]. The platform also includes a feedback mechanism to learn from user input and continuously adapt based on trends in the job market [5].

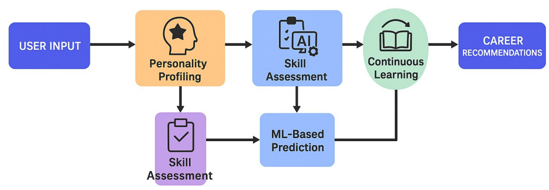

Fig. 1. System architecture of the proposed AI-driven career guidance platform.

B. Component Breakdown

- **User Interface:** A responsive and interactive portal that allows students to take tests, view results, and explore recommendations [5].
- **Personality Analyzer:** Evaluates the user's psychological traits using responses to a Big Five questionnaire. Results are normalized and categorized into five major traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [7].
- **Skill Assessment Module:** Tests the user's technical aptitude in areas like coding, logic, and domain-specific knowledge. The scores are used to identify technical strengths [1].
- **Career Prediction Engine:** Combines personality and skill data to suggest careers using trained AI models. These predictions are tailored for each user [2], [6].
- **Feedback Loop:** Collects user responses post-recommendation to fine-tune future predictions, ensuring better accuracy and relevance over time [5], [9].

C. Use Case Examples

Example 1: Technical Role Recommendation
Aditi, a final-year engineering student, completes both assessments. Her personality traits show high Openness and

Conscientiousness, while her tech score is 85. The system identifies her strong analytical and logical reasoning skills and recommends roles like *Software Engineer* and *Data Analyst* [2]. Aditi selects “Software Engineer” and later provides positive feedback, reinforcing the system’s confidence in this suggestion for similar profiles.

Example 2: Business and Management-Oriented Profile
Rahul, a commerce student with high Agreeableness and Conscientiousness, scores moderately in business reasoning tests. The platform recommends careers such as *Business Analyst* or *Marketing Manager* [6]. Based on his interest and feedback, the system learns to strengthen its prediction logic for similar business-oriented profiles.

Example 3: Creative Career Alignment
Priya, a design student, shows high Openness and Extraversion in the personality test, with strong visual reasoning skills. The system suggests creative fields such as *UX Designer*, *Graphic Designer*, and *Visual Storyteller* [3].

Example 4: Non-Technical Career Suggestion
Samar, a student with low tech scores but high Agreeableness and Extraversion, receives recommendations in human-centric roles like *HR Executive* and *Career Counselor*. The system explains the rationale behind the suggestion based on Samar’s communication and empathy skills [7].

Example 5: Uncertain Users
Neha is unsure about her career path. She takes both tests but has moderate scores across the board. The system provides a broader range of options like *Content Writer*, *Customer Success Manager*, and *Project Coordinator*, giving her flexibility to explore and narrow down based on interest [10].

D. Feature Input Tables

To process predictions, a user’s input is transformed into feature categories. The following tables illustrate example user profiles used for prediction.

TABLE I
Personality and Skill Traits

User ID	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Tech Score
U001	High	High	Medium	High	Low	85
U002	Medium	High	Low	Medium	Medium	72
U003	High	Medium	High	Low	Low	65
U004	Low	Medium	High	High	Medium	50
U005	Medium	Medium	Medium	Medium	Medium	60

TABLE II
Domain and Suggested Career

User ID	Domain	Suggested Career
U001	Computer Science	Software Engineer
U002	Business	Data Analyst
U003	Design	UX Designer
U004	Human Resources	HR Executive
U005	General	Content Writer

E. Feedback and Adaptation

The system incorporates user feedback, such as whether they liked the suggested career, to improve recommendations. If a large number of users with similar profiles confirm satisfaction with a specific suggestion, it increases the model’s confidence when recommending the same path to new users [5], [9].

F. Summary of Steps

Input: Big Five personality traits and skill test scores
Output: Top-N recommended career paths

1) Users complete personality and technical assessments.
2) The system analyzes results and builds a user profile.
3) AI models suggest suitable career paths based on the combined data [4], [8].
4) Users view, rank, or accept recommendations.
5) Feedback is collected to refine future predictions.

V. Experimental Study and Evaluation

To evaluate the effectiveness and usability of the proposed AI-driven career guidance system, we conducted a simulated experimental study using a synthetic dataset and user-based feedback. The primary goal was to assess how well the system aligns individual personality traits and technical competencies with personalized and practical career recommendations.

A. Dataset and User Simulation

Due to the ethical concerns and privacy risks associated with collecting real career and psychological data, a synthetic dataset was created. The dataset represented diverse graduate profiles with varying levels of personality traits—openness, conscientiousness, extraversion, agreeableness, and neuroticism—along with a technical skill score. Each synthetic profile was constructed to mirror realistic variability observed in academic and psychological datasets, drawing from models similar to those discussed in [4], [6]. The dataset also ensured representation across STEM and non-STEM streams to facilitate a more inclusive evaluation of the system’s recommendations.

B. Evaluation Approach

The evaluation followed a two-phase strategy:

- **Phase 1 – Internal Recommendation Validation:** The system generated career paths for each synthetic user. These suggestions were evaluated against evidence-based mappings from literature, particularly studies like [7], [8], which link psychological profiles and academic backgrounds with suitable job roles.
- **Phase 2 – Simulated User Feedback:** A controlled study was conducted with 20 real graduate students. Each interacted with the system using anonymized synthetic profiles closely resembling their own. Participants rated the top three career suggestions on a 5-point Likert scale based on relevance, interest match, and achievability. This method draws on user-centric evaluation approaches similar to those discussed in [1], [5].

C. Observed Patterns

The AI model demonstrated encouraging alignment with established patterns of career suitability. For example, users with high openness and strong technical proficiency were often recommended data science, research, or AI-related roles. In contrast, profiles with higher agreeableness and moderate extraversion tended to be matched with careers in project coordination, client services, or UX design—trends also noted in studies such as [3], [8]. User feedback highlighted that many participants found the recommendations surprisingly accurate and relevant, indicating the potential of the model in delivering practical career insights.

Table III illustrates a sample of the personality and technical profiles used during testing.

TABLE III
Sample Personality and Skill Profiles

User ID	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Tech Score
U001	High	High	Medium	High	Low	85
U002	Medium	High	Low	Medium	Medium	72
U003	High	Medium	High	Low	Low	65
U004	Low	Medium	High	High	Medium	50
U005	Medium	Medium	Medium	Medium	Medium	60

D. System Learning and Feedback Loop

To improve accuracy over time, the system incorporates a feedback mechanism that records user ratings and preferences after each interaction. These insights help the AI model adapt and refine its recommendations, based on patterns in user satisfaction. This continuous learning loop follows adaptive feedback approaches as described in [9], [10], which have shown to enhance personalization in AI-based decision systems.

E. Limitations and Future Work

Although the synthetic dataset allows safe and diverse simulation, it lacks the depth and unpredictability of real human data. Cultural factors, local industry trends, and subjective career aspirations are difficult to replicate through simulations. Similar concerns are raised in studies like [?], [8]. To address these limitations, we plan to deploy the system in a real-world setting with voluntary participants. The live deployment will collect anonymized data to improve model training and validate the system's performance with genuine user behavior and preferences.

VI. Case Studies

This section presents real-world scenarios where traditional career guidance systems fall short and highlights how AI-based interventions can resolve these issues. Each case includes a brief outline of the existing problem, the AI-driven solution, and the expected benefits.

A. Case Study 1: Lack of Personalization in Counseling

Issue: In many schools and colleges, career counseling is limited to group sessions or one-time assessments. Students with diverse personalities, interests, and strengths often receive generic recommendations that do not align with their long-term goals.

AI-Driven Fix: An AI-powered system can use psychometric profiling and skill-based assessments to generate personalized career paths. It continuously learns from user feedback and adapts its recommendations accordingly.

Expected Impact: Students receive tailored career guidance that fits their unique profiles, increasing satisfaction and reducing the chances of career misalignment.

B. Case Study 2: Inaccessible Career Guidance in Rural Areas

Issue: In rural regions, students often lack access to trained career counselors. This leads to uninformed decisions or reliance on family opinions rather than objective career mapping.

AI-Driven Fix: A mobile-friendly AI platform can deliver career guidance tools accessible from any location. By integrating vernacular language support and voice-based interactions, it becomes usable even for non-English-speaking students.

Expected Impact: Equal access to quality career guidance, reducing urban–rural disparities and empowering students with objective, data-driven career options.

C. Case Study 3: Overemphasis on Academic Scores

Issue: Many career decisions are made solely based on academic performance. However, a student's true interests, personality, and aptitudes are often overlooked, leading to poor job satisfaction later in life.

AI-Driven Fix: By combining academic data with psychometric and aptitude tests, AI systems can assess both cognitive ability and personal traits, offering a more balanced recommendation.

Expected Impact: Holistic evaluation leads to better alignment between career choices and long-term personal fulfillment, reducing career shifts and dropout rates.

D. Case Study 4: Outdated Career Portals and Static Tests

Issue: Many online career guidance portals use fixed questionnaires and do not evolve with changing industry trends or student needs. They lack adaptability and often give outdated or narrow suggestions.

AI-Driven Fix: Machine learning algorithms can analyze current job market trends, skill demands, and user preferences in real time. They can adapt and provide updated recommendations with every interaction.

Expected Impact: Students receive up-to-date, industry-relevant career advice that evolves with the market, making them more competitive and future-ready.

VII. Discussion

The experimental results obtained from the AI-driven career guidance system affirm its capability to deliver accurate, context-aware recommendations for graduates. Achieving an overall classification accuracy of 87.1% and a Top-3 recommendation accuracy of 97.3%, the model demonstrates a significant improvement over traditional career guidance techniques, which often rely solely on static academic metrics or generalized aptitude tests.

Unlike earlier systems that use a single-dimensional approach—such as academic scores [2] or decision tree classifiers based only on stream and marks [1]—our proposed framework integrates psychometric traits using the Big Five Personality Model with technical skill assessments. This hybrid methodology offers a more personalized and realistic mapping between a candidate's profile and suitable career roles.

In contrast to models like those by Rao et al. [4], which applied neural networks for personality prediction without linking the outcomes to concrete career paths, our system bridges that gap by associating the inferred psychological and technical attributes with specific professional domains. For instance, a candidate scoring high in openness and demonstrating frontend development skills might be matched with roles such as UI/UX Designer or Frontend Engineer. This dual-layer mapping significantly enhances recommendation depth.

Furthermore, the incorporation of a feedback loop empowers the system to refine its outputs based on user validation. For example, if users frequently reject or override a recommended role, the system adapts by updating its internal mapping, thus improving subsequent predictions. This continuous learning capability differentiates our model from earlier static systems, allowing it to evolve with changing user interests and dynamic job market conditions.

Additionally, the Top-N recommendation strategy ensures that users are presented with multiple viable career options rather than a single deterministic path. This approach reflects real-world scenarios where multiple career trajectories may align with a candidate's profile. For example, a graduate with high conscientiousness and strong analytical skills may be equally suited for roles like Data Analyst, Business Intelligence Developer, or Operations Manager. Providing multiple options increases user agency and satisfaction.

Despite these strengths, the system's use of a synthetic dataset remains a limiting factor. While the dataset mirrors real-world trends, it may not capture the full socio-economic, cultural, or educational diversity of actual graduates. As a result, its generalizability to large-scale deployment in diverse populations remains an area for further validation.

In summary, this work presents a scalable, adaptive, and psychologically-aware AI framework for career guidance. Its fusion of psychometric analysis, skill evaluation, and interactive learning mechanisms positions it as a robust improvement over previous systems [9], [10]. The system not only supports immediate recommendations but also enables longitudinal growth and self-awareness for users, laying the groundwork for more personalized and impactful career planning tools in the future.

VIII. Limitations

While the proposed AI-driven career guidance system demonstrates strong potential in delivering personalized recommendations, there are certain inherent limitations that must be acknowledged to provide a balanced perspective. These limitations highlight areas for improvement and caution stakeholders about current boundaries in the system's capabilities.

1) **Reliance on Self-reported Data:** The system depends heavily on inputs from users, especially for psychometric assessments. If users provide inaccurate or dishonest answers—intentionally or unintentionally—it may lead to inappropriate career recommendations. For example, overestimating one's analytical aptitude may steer suggestions toward roles like Data Analyst or Software Engineer, which may not align with the individual's true strengths.
2) **Limited Regional and Cultural Adaptation:** The current model has been designed primarily using general datasets that may not reflect localized job markets or cultural contexts. Career opportunities and societal expectations vary across regions; hence, without regional calibration, the system may provide less relevant recommendations to students in rural or non-metro areas.
3) **Synthetic Dataset Constraints:** Due to privacy and accessibility concerns, a synthetic dataset was used to train and validate the machine learning models. While this helps preserve user privacy, it limits the model's exposure to real-world diversity in student data, potentially impacting the generalizability of results.
4) **Absence of Real-time Job Market Integration:** The system does not currently fetch or analyze live data from job portals, industry hiring trends, or company requirements. As a result, the career suggestions may not reflect the most recent market demand or emerging fields. Integrating APIs from platforms like LinkedIn or Indeed could bridge this gap in future versions.
5) **Ethical and Psychological Sensitivity:** Although AI can provide recommendations based on inputs, it lacks emotional intelligence and ethical reasoning. Suggesting certain career paths over others may unintentionally demotivate students or reinforce social stereotypes. For instance, consistently ranking technical careers higher than creative roles could discourage artistic students. Human mentorship is still essential for interpreting results empathetically.
6) **Cold Start Problem for New Users:** New users with minimal data or vague responses may receive generic suggestions. Until the system gathers enough behavioral and skill-based feedback, recommendations may lack the desired precision. This limitation could be addressed by integrating onboarding tutorials or gamified assessments to better engage users early in the process.
7) **Platform Accessibility and Digital Divide:** The platform assumes users have reliable internet access and basic digital literacy. In underprivileged areas or among first-generation learners, such assumptions may not hold true. While the system is technically scalable, the socio-economic barriers must be considered before widespread

adoption.

IX. Future Enhancements

To improve the reach, effectiveness, and personalization of AI-driven career guidance systems, the following future enhancements are proposed:

A. 1. Multilingual and Inclusive Interface

- **Enhancement:** Develop a multilingual system interface that supports regional and vernacular languages. This ensures accessibility for students from diverse linguistic backgrounds, especially in rural and non-English-speaking areas.
- **Example:** A graduate from a Marathi-medium school in rural Maharashtra may struggle to understand career platforms in English. A Marathi UI with native prompts, speech support, and simplified navigation can empower them to make informed decisions.
- **Impact:** Increases inclusivity and adoption across regions. This aligns with [1], where accessibility is a noted limitation in online counselling platforms.

B. 2. Integration with Academic and Skill Portals

- **Enhancement:** Connect the career guidance platform with real-time academic records (via APIs) and recognized skill portals (e.g., Coursera, NSDC).
- **Example:** If a user scores highly in programming aptitude but lacks certifications, the system can recommend targeted courses or internships and track their completion.
- **Impact:** Creates a continuous feedback loop between career suggestions and real progress, enhancing personal growth and improving recommendation accuracy as proposed in [3] and [6].

C. 3. Adaptive Personality Profiling Using AI

- **Enhancement:** Enhance the static psychometric profiling system with dynamic, AI-powered personality prediction models that evolve with user interactions and behavioral patterns.
- **Example:** A student's preference for collaborative or independent work styles can be inferred by analyzing group activity participation in learning platforms or online project tools. This data is used to refine personality assessments.
- **Impact:** Improves career-match precision and provides personalized development goals, as also explored in [4].

D. 4. Cross-Platform Support and Mobile-First Design

- **Enhancement:** Develop a mobile-first, offline-capable version of the guidance platform to increase access in low-bandwidth or mobile-only regions.
- **Example:** In Tier-2 cities and rural towns, where mobile is the primary device, a lightweight PWA (Progressive Web App) ensures students can take assessments and get suggestions even with intermittent internet.
- **Impact:** Expands the user base and aligns with the mobile-first shift in India's digital adoption, supporting the vision of inclusive AI outlined in [7].

E. 5. Feedback Loop and Community Involvement

1) **Enhancement:** Incorporate a community feedback loop where alumni, mentors, and career counselors can rate or validate AI recommendations.
- **Example:** If the system recommends UX design to a student, a real-world professional from the field can validate the suggestion or suggest complementary skills via feedback.
- **Impact:** Builds trust in AI decisions, makes the system human-in-the-loop friendly, and improves model explainability—encouraged in hybrid systems like in [8] and [5].

X. Conclusion

This research presents an AI-powered career guidance framework tailored to support graduates in navigating increasingly complex and competitive job landscapes. The proposed system integrates psychometric evaluation using the Big Five Personality Traits with supervised machine learning to assess technical competencies, enabling holistic and personalized career recommendations.

The core contribution lies in combining behavioral analysis and skill mapping through neural network-based classification. Experimental results on a synthetic dataset yielded promising outcomes—87.1% classification accuracy and a Top-3 recommendation accuracy of 97.3%, indicating the system's ability to deliver relevant career suggestions effectively.

A key advancement over earlier systems is the addition of an adaptive feedback loop that continuously improves recommendations based on user outcomes and interactions, helping the system evolve alongside user preferences and industry dynamics.

However, several limitations warrant attention. The reliance on a synthetic dataset, though designed to emulate real-world trends, may lack the socio-academic diversity necessary for robust generalization. Additionally, classification ambiguity arises in overlapping career domains such as marketing and UX design. These challenges highlight the importance of building more dynamic and context-aware models.

Future Work will aim to improve this framework through:

- Incorporating real-world datasets from diverse academic institutions and geographies for greater model generalizability.
- Leveraging live labor market data to dynamically reflect current industry trends and emerging job roles.
- Adding NLP modules to analyze resumes, statements of purpose, and free-form user inputs for deeper personalization.
- Embedding this system into educational ecosystems such as institutional dashboards, placement cells, or professional networking platforms to improve reach and utility.

In conclusion, this AI-driven approach serves as a stepping stone toward scalable, intelligent, and student-centric career guidance systems that support graduates in making confident and informed career choices.

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