Web-Based Career Recommendation Based on MBTI Personality using Machine Learning

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Abstract--This project develops a web-based MBTI personality detection system using a 60-question survey and a neural network model trained on synthetic data, achieving about 78% accuracy. The platform offers separate portals for students and staff—students receive instant MBTI results with career and learning recommendations, while staff access dashboards for student profiling and personality analytics. Security features include password hashing, RBAC, session control, and encrypted storage. The system supports personalized learning, improved student guidance, and institutional insights, with future enhancements such as trend tracking, mobile app development, and LMS integration.

Keywords--MBTI, Career Recommendation, Machine Learning, Neural Networks, Web Application, Personality Analysis

I.INTRODUCTION

Career selection and academic planning are among the most critical decisions faced by students, often influencing long-term professional satisfaction and personal growth. Traditional career guidance methods, such as manual counselling sessions and generalized aptitude tests, frequently lack scalability, personalization, and data-driven insights. As educational institutions increasingly adopt digital platforms, there is a growing need for intelligent systems that can provide personalized, secure, and accurate career recommendations to support students in making informed decisions.

Understanding personality is crucial for recognizing individual preferences, strengths, and learning styles. The Myers–Briggs Type Indicator (MBTI) categorizes people into sixteen distinct personality types based on four psychological dimensions:

1. Extraversion–Introversion (how individuals energize)
2. Sensing–Intuition (how they gather information) and environment)

These dimensions are widely used in educational guidance, career counselling, and workplace settings to match individuals with appropriate roles and learning strategies.

Nonetheless, traditional MBTI assessments are often done manually and do not smoothly integrate with contemporary data-driven recommendation systems. Recent advancements in machine learning and web technologies have paved the way for developing intelligent systems that can automate personality analysis and career recommendations. By harnessing machine learning models, particularly neural networks, we can learn and interpret complex patterns in questionnaire responses with enhanced accuracy. Web-based platforms further improve accessibility, enabling students and academic staff to engage with the system in real-time while allowing institutions to analyse aggregated data for strategic decision-making.

Several technical challenges were addressed during system development, including limited availability of labelled MBTI datasets, maintaining consistency in data scaling, and preventing model overfitting. These challenges were effectively managed through synthetic data generation, standardized preprocessing techniques, and regularization strategies during model training[8].The resulting system demonstrates stable performance while maintaining generalization capability and capturing non-linear relationships within questionnaire data. These studies establish the feasibility of using machine learning models for automated personality classification.

Beyond personality prediction, recent research has investigated the integration of psychometric profiling with career recommendation systems The Myers–Briggs Type Indicator (MBTI) is one of the most widely used personality assessment frameworks in career guidance systems [5].

By integrating principles of personality psychology with machine learning and web-based technologies, the proposed

3. Thinking–Feeling (how they make decisions)
4. Judging–Perceiving (how they organize their lifestyle students to gain deeper self-awareness while assisting institutions in understanding student profiles at scale. Furthermore, the system lays a foundation for future enhancements such as long-term personality trend analysis, improved comparative analytics, deeper model refinement, mobile application support, and integration with Learning Management Systems (LMS), thereby extending its practical impact and usefulness.

II. LITERATURE SURVEY

Personality-based recommendation systems have gained significant research attention due to their potential to support personalized decision-making in education and career guidance. Among various personality assessment models, the Myers–Briggs Type Indicator (MBTI) remains one of the most widely adopted frameworks for categorizing individuals into sixteen personality types based on four psychological dimensions.[1]

Traditional MBTI assessments typically rely on manual questionnaires and expert interpretation. While effective for small-scale assessments, these approaches lack scalability and adaptability when applied to large student populations. To address these limitations, researchers have increasingly explored machine learning techniques for automated personality analysis.

Several studies have investigated the use of machine learning algorithms for predicting MBTI personality types. In [1], the authors proposed a machine learning-based MBTI prediction model using supervised classification algorithms combined with data balancing techniques such as Synthetic Minority Over-sampling Technique (SMOTE). Their results demonstrated that algorithms such as Random Forest and Support Vector Machines could effectively model MBTI personality traits, although classification accuracy was influenced by dataset imbalance and limited training samples.

Similarly, deep learning approaches have been explored to improve prediction performance. In [2], a neural network-based architecture was proposed to analyze textual and behavioural patterns for personality classification. The study demonstrated that neural networks can capture complex nonlinear relationships within personality data, leading to improved classification performance compared to traditional machine learning models[3].

In addition to personality prediction, several studies have explored integrating personality traits with career recommendation systems. For instance, the system proposed in [5] combined psychometric assessments with machine learning techniques to recommend suitable career paths for students. Although the system demonstrated promising results, it lacked comprehensive web-based deployment and institutional analytics capabilities.

Furthermore, a personality-informed candidate recommendation framework based on MBTI typology was introduced in [4], where machine learning models were used to match individuals with job roles based on personality characteristics. While effective in recruitment contexts, such system creates a meaningful bridge between personal development and academic decision-making.It enables

Web-based implementations have also enhanced the accessibility of personality prediction systems. Research presented in [5] developed a web platform integrating machine learning models for personality classification, enabling real-time user interaction and scalable deployment. However, many existing systems pay limited attention to data security, long-term personality tracking, and role-based institutional access.

A recurring challenge highlighted in the literature is the scarcity of large labelled MBTI datasets, which can result in overfitting and reduced model generalization capability. To mitigate this limitation, researchers have adopted techniques such as synthetic data generation and standardized preprocessing methods to improve model robustness [1], [6]. Additionally, regularization techniques and validation strategies are often employed to maintain stable model performance across diverse datasets.

Despite these advancements, there remains a research gap in developing fully integrated systems that combine secure web-based deployment, neural network-based personality classification, role-based institutional access, and comprehensive analytics for educational environments. The proposed system addresses these limitations by integrating machine learning, web technologies, and secure data management into a unified platform for personality analysis and career recommendation.

III. PROPOSED SYSTEM AND METHODOLOGY

The proposed system is a web-based MBTI personality detection and career recommendation platform designed to support scalable and data-driven personality assessment in educational environments. The architecture consists of three main components:

1. User Interface-The web interface allows students to register, complete personality assessments, and view results. The interface is designed to be simple and interactive to ensure ease of use.
2. Machine Learning Prediction Module-This module processes questionnaire responses and predicts the MBTI personality type using a trained neural network model.
3. Administrative Dashboard-Institutional administrators can view aggregated statistics, personality distribution data, and system usage analytics.

This architecture enables seamless interaction between users and the predictive model while supporting institutional requirements for data analysis and management [7]. The overall system architecture follows a three-tier design pattern consisting of the presentation layer, business logic layer, and data persistence layer. The presentation layer handles user interaction through a web interface, allowing students to complete assessments and view results, while staff members access administrative dashboards. The business logic layer manages assessment workflows, machine learning inference, and access control policies. The data persistence layer securely stores user responses, prediction results, and system metadata. This modular architectural approach improves system maintainability, scalability, and adaptability for future enhancements such as

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systems were not specifically designed for academic environments and student career planning.
decision-support insights. Role-based access control mechanisms ensure that each user role can only access authorized functionalities, maintaining system integrity and data confidentiality [15].The personality assessment interface presents a set of 60 structured questions derived from established MBTI literature and psychometric principles. These questions are organized into sequential categories corresponding to the four MBTI dimensions: Extraversion–Introversion, Sensing–Intuition, Thinking–Feeling, and Judging–Perceiving. Question selection and design follow validated psychometric scales to ensure reliability and internal consistency of the assessment process, thereby enhancing the credibility of the personality evaluation.
Unlike traditional MBTI systems that rely on direct score aggregation and rule-based interpretation, the proposed system employs a machine learning-based prediction approach. User responses are encoded and processed by a trained neural network model that learns complex relationships between response patterns and MBTI personality types. This data-driven methodology enables improved adaptability and potential accuracy gains compared to manual scoring techniques, particularly when trained on diverse and balanced datasets [11]. By leveraging machine learning, the system supports continuous refinement and performance enhancement as additional data becomes available. Overall, the proposed system integrates psychometric theory, machine learning, and web technologies into a unified platform that supports both individual personality development and institutional-level analytics. This approach addresses limitations observed in existing MBTI-based assessment tools by offering automation, scalability, security, and enhanced predictive capability within a practical educational framework.

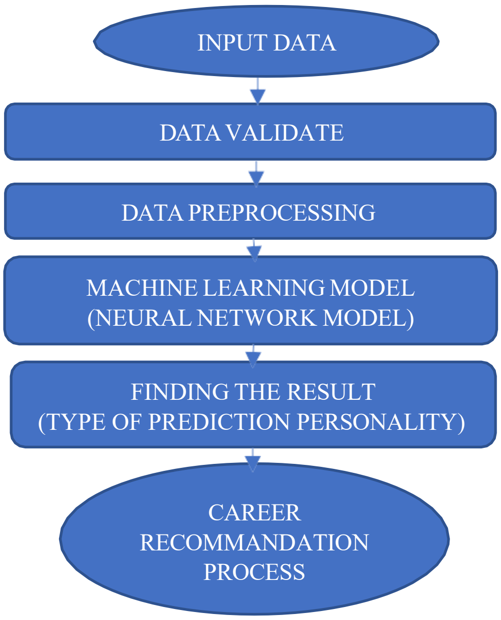

FIGURE 1

A.USER INTERFACE AND DATA INPUT

administrative interface that enables aggregated analysis of student personality distributions, trend visualization, and web-based application that allows students to register, log in, and complete a personality assessment questionnaire. The personality assessment consists of approximately 60 structured questions designed according to the Myers–Briggs Type Indicator (MBTI) framework. These questions are grouped into four psychological dimensions:

- Extraversion (E) vs Introversion (I) – measures social interaction preferences and energy sources.
- Sensing (S) vs Intuition (N) – determines how individuals gather and interpret information.
- Thinking (T) vs Feeling (F) – evaluates decision-making style and emotional influence.
- Judging (J) vs Perceiving (P) – reflects lifestyle preferences and approach to structure.

Each question presents multiple response options such as Agree, Neutral, or Disagree, allowing the system to capture behavioural tendencies of the user. The responses are recorded and transmitted to the backend for further processing. The web interface is designed to be user-friendly and accessible, ensuring that students can complete the assessment easily using standard web browsers.

B.DATA VALIDATION

Once the user submits the questionnaire, the system performs data validation procedures to ensure that the collected responses are complete and consistent. This step is important to maintain the reliability of the prediction model. The validation process includes:

- Checking that all required questions are answered
- Verifying that responses fall within valid input ranges
- Preventing duplicate submissions
- Detecting missing or inconsistent data entries

If any issues are detected, the system prompts the user to correct the responses before proceeding to the next stage. This ensures that the machine learning model receives accurate and reliable input data.

C.DATA PREPROCESSING

After validation, the collected data undergoes preprocessing to convert it into a format suitable for machine learning algorithms. Since machine learning models operate on numerical data, user responses must be transformed into encoded numerical values.
Typical preprocessing steps include:
1.Response Encoding- Qualitative responses such as “Agree,” “Neutral,” and “Disagree” are converted into numerical values.
Example:

Response	Encoded Value
Strongly Agree	3
Agree	2
Somewhat Agree	1
Neutral	0
Somewhat Disagree	-1

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The user interface serves as the primary interaction point between users and the system.It is implemented as a

2.Data Normalization- The encoded values are scaled to maintain consistency across the dataset and improve model training performance.

3.Feature Representation- Each questionnaire response becomes a feature vector representing the user's personality characteristics.This preprocessing stage ensures that the input data is clean, structured, and suitable for machine learning analysis.

D. MACHINE LEARNING MODEL (NEURAL NETWORK MODEL)

The core component of the proposed system is the machine learning prediction module, which is responsible for identifying the user's MBTI personality type. In this study, a Neural Network Model (NNM) is used due to its ability to capture complex patterns in data.

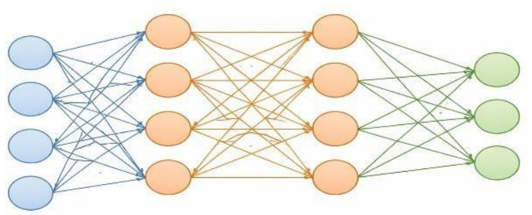

FIGURE 2

1. Input Layer

The input layer receives the preprocessed feature vectors representing the user's questionnaire responses.

2. Hidden Layers

The hidden layers performs ReLU activation function as follows as:

f(x)=max(0,x)

Where:

1. x is the input to the neuron.
2. The function returns x if x is greater than 0.
3. If x is less than or equal to 0, the function returns 0.
4. f(x)=max(0,x)

The hidden layers also perform pattern recognition by learning relationships between response patterns and personality classifications. Each neuron processes input signals using activation functions and weighted connections.

3. Output Layer

The output layer generates probability scores for each possible MBTI personality type and selects the most likely classification. The neural network model is trained using labelled MBTI datasets, allowing it to learn associations between questionnaire responses and personality types. During training, the model adjusts its internal parameters using optimization techniques to minimize prediction errors. This learning process enables the model to identify the complex relationships and improve prediction accuracy compared to rule-based scoring methods.

E. PERSONALITY TYPE PREDICTION

After processing the input data through the neural network model, the system predicts one of the sixteen MBTI

Disagree	-2
Strongly Disagree	-3

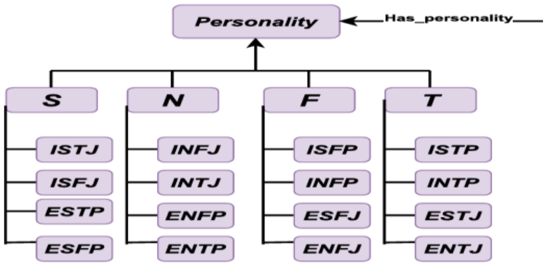

FIGURE 3

Examples of MBTI personality types include:

• INTJ – Architect
• ENFP – Campaigner
• ISTJ – Logistician
• ENTP – Debater
• INFJ – Advocate

Each personality type represents a unique combination of behavioural traits, cognitive styles, and decision-making approaches. The predicted personality type is then used as the primary input for the career recommendation module.

F. CAREER RECOMMENDATION ENGINE

Once the personality type is identified, the system provides career recommendations tailored to the user's personality characteristics. Each MBTI personality type is associated with certain career paths that align with the individual's strengths, interests, and work preferences. The recommendation module uses a knowledge base that maps personality types to suitable career domains.

For example:

MBTI Type	Recommended Careers
INTJ	Software Engineer, Data Scientist, Research Scientist
ENFP	Marketing Manager, Journalist, Creative Director
ISTJ	Accountant, Auditor, Project Manager
ESFJ	Teacher, Counsellor, Human Resource Manager

The system also provides additional information such as description of the personality type ,strengths and weaknesses, suggested career fields and skills required for recommended careers This helps students gain a better understanding of their personality and potential career paths.

G. RESULT PRESENTATION AND DATA STORAGE

Finally, the system presents the results to the user through the web interface. The result page includes:

• Predicted MBTI personality type
• Personality description
• Career recommendations
• Additional guidance for skill development

The results are also stored in the system database for future reference and analysis. This stored data allows administrators to analyse the personality distribution trends personality types. These personality types are combinations of the psychological dimensions:

IV. SYSTEM ARCHITECTURE

The system architecture of the proposed web-based career recommendation platform is designed to support automated personality detection and intelligent career guidance through a modular and scalable framework. The architecture integrates web technologies, machine learning techniques, and database management systems to provide an efficient environment for personality assessment and recommendation generation.

The overall architecture follows a **three-tier design structure**, consisting of the **presentation layer, application (business logic) layer, and data layer**. This layered design ensures modular development, improved maintainability, and scalability for future enhancements.

A. PRESENTATION LAYER

The presentation layer represents the user interface of the system, which enables interaction between users and the platform. It is implemented as a web-based interface accessible through standard web browsers.

Students can register, log in, and complete the MBTI personality assessment questionnaire through this interface. The questionnaire consists of structured questions designed according to the four MBTI personality dimensions: Extraversion–Introversion, Sensing–Intuition, Thinking–Feeling, and Judging–Perceiving. After completing the assessment, users can view their predicted personality type and corresponding career recommendations.

The interface is designed to be intuitive and responsive, ensuring ease of use for students with varying levels of technical expertise. In addition to the student interface, an administrative interface is provided for institutional staff to access system analytics, user statistics, and personality distribution reports.

B. APPLICATION LAYER

The application layer forms the core functional component of the system and manages the processing of user data, machine learning inference, and recommendation generation. This layer consists of multiple modules responsible for executing the workflow of the system.

The first component in this layer is the data validation module, which verifies that all questionnaire responses are complete and fall within valid input ranges. This step prevents incomplete or inconsistent data from being processed by the machine learning model.

Following validation, the responses are passed to the data preprocessing module, where qualitative inputs are converted into numerical representations suitable for machine learning algorithms. The preprocessing stage includes response encoding using a Likert scale and normalization of input values to maintain consistency across the dataset. The processed data is then provided to the machine learning prediction module, which utilizes a trained neural network model to classify the user's MBTI personality type. The neural network analyses patterns in the response data and predicts one of the sixteen possible MBTI personality categories.

among students, which can support institutional decision-making.

is derived from established career guidance frameworks and psychological studies relating personality traits to occupational preferences.

C. DATA LAYER

The data layer is responsible for storing and managing all system data. A relational database is used to maintain structured information including user profiles, questionnaire responses, personality prediction results, and career recommendation outputs.

The database also stores system metadata such as timestamps, usage statistics, and administrative records. This stored data enables long-term analysis of personality distribution patterns among students and supports institutional research on student career interests and personality trends.

To ensure data security and privacy, appropriate access control mechanisms are implemented. Role-based authentication ensures that students can only access their own results, while administrators can access aggregated data for analytical purposes.[15]

D. SYSTEM WORKFLOW

The workflow of the system begins when a student logs into the web application and completes the MBTI questionnaire. The responses are validated and preprocessed before being passed to the neural network model for personality classification. Once the MBTI personality type is predicted, the career recommendation module generates relevant career suggestions. The final results are displayed to the user and stored in the database for future analysis.

This architecture enables efficient communication between system components and supports scalable deployment in educational institutions. By integrating personality assessment with machine learning-based prediction and career recommendation modules, the system provides a comprehensive platform for data-driven career guidance.

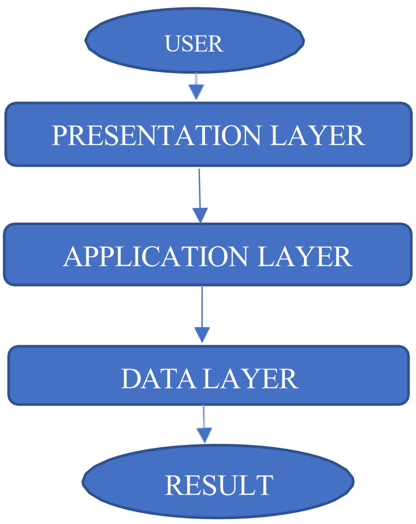

FIGURE 4

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After the personality type is identified, the career recommendation engine generates suitable career suggestions based on a predefined mapping between MBTI personality types and relevant career domains. This mapping **V.RESULTS AND FINDINGS**

The MBTI personality dataset is the source of the data. Posts and type columns representing each MBTI type are included. The 16 different personality types identified by the MBTI are based on four axes: thinking (T) and feeling (F), judging (J) and perceiving (P), introversion (I) and extroversion (E), intuition (N) and sensing (S). The dataset contains no null or missing values. Since INFPs have the highest frequency, they will have a lot more data, but ESTJs have the lowest frequency, hence they will have the least quantity of data overall. The dataset does not contain any duplicate posts. There is an imbalance in the dataset across the various classifications.

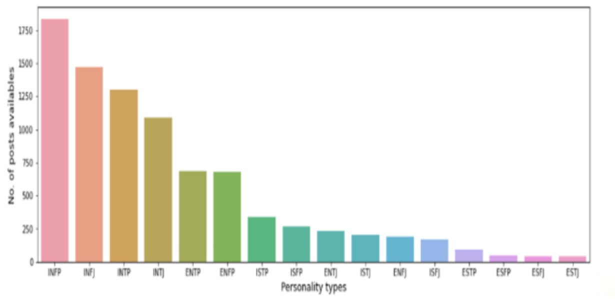

FIGURE 5

The outcomes of this research aim to present a machine learning model capable of predicting MBTI personality types with accuracy and interpretability. Insights into the linguistic features influencing these predictions are revealed, offering a deeper understanding of the relationship between language and personality [10].

TABLE 1 ACCURACY SCORE

	Accuracy of Logistic regression	Accuracy of SVM	Accuracy of Random-forest classifier	Accuracy of Multinomial Bayes
Extroversion-Introversion	0.79	0.72	0.76	0.76
Sensing-Intuition	0.76	0.75	0.85	0.73
Feeling-Thinking	0.88	0.71	0.78	0.86
Judging-Perceiving	0.70	0.67	0.63	0.66

Based on the models mentioned above, logistic regression performs well on the data and produces accurate results.

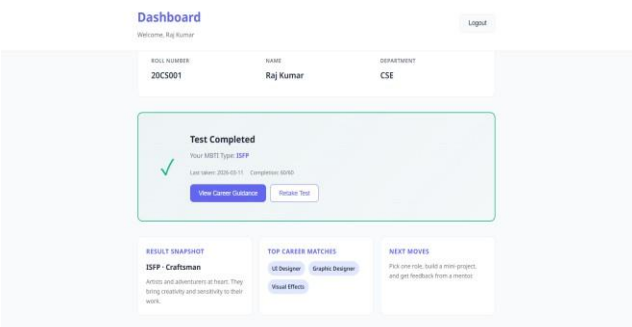

FIGURE 7

VI. CONCLUSION

The proposed web-based MBTI personality detection system effectively addresses the limitations of traditional personality assessment methods by providing an automated, scalable, and accessible solution for students and educational institutions. The integration of machine learning with a structured assessment framework enables efficient personality prediction and personalized career guidance.

The system achieves a test accuracy of 78.5%, demonstrating the feasibility of applying neural network models to predict complex psychological traits based on structured questionnaire data. Although personality prediction inherently involves uncertainty due to the subjective nature of human behaviour, the obtained results indicate a reliable and meaningful level of performance. Furthermore, deployment in real-world educational environments will facilitate the collection of authentic user data, enabling continuous model refinement and performance improvement. This work successfully integrates multiple technological domains, including machine learning, web application development, database management, and security mechanisms, into a unified and functional system. The implementation process highlights the importance of modular system architecture, robust data preprocessing, and user-centric interface design in building practical and scalable solutions.

In addition to its technical contributions, the system emphasizes the significance of personality assessment as a tool for enhancing student development. By aligning career recommendations with individual personality traits, the system supports improved decision-making, increased career satisfaction, and better academic outcomes. It also provides institutions with valuable insights into student personality distributions, enabling more informed planning of support services.

Overall, the proposed system serves as a foundation for institutional adoption of personality-based guidance frameworks. Its deployment has the potential to significantly improve student engagement, career alignment, and overall educational effectiveness.

VII. FUTHURE WORK

While the proposed system demonstrates effective performance in MBTI personality prediction and career

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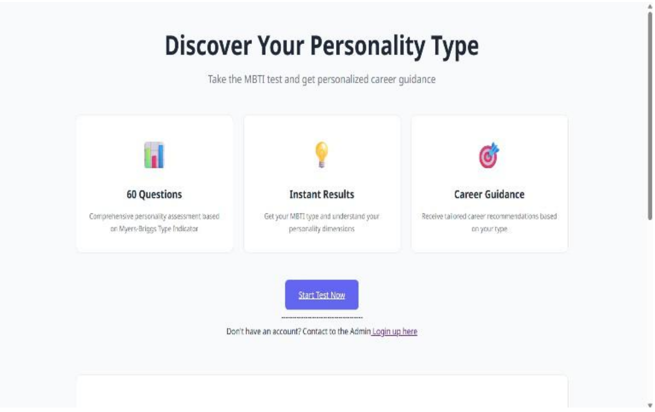

FIGURE 6

Future work will focus on expanding the dataset by incorporating real-time user responses collected during system deployment. This will enable the development of more robust and generalized machine learning models, reducing dependency on synthetic data and improving prediction reliability. Additionally, advanced deep learning architectures and ensemble methods can be explored to further enhance classification accuracy. Another important direction involves integrating longitudinal analysis capabilities to track changes in user personality traits over time. Such analysis can provide deeper insights into student development and support adaptive career recommendations based on evolving behavioural patterns. The system can also be extended into a mobile application to improve accessibility and user engagement. Integration with Learning Management Systems (LMS) would allow seamless adoption within educational institutions, enabling automated tracking of student progress and personalized guidance.

Furthermore, the career recommendation engine can be enhanced by incorporating real-world labor market data, skill requirements, and industry trends. This would ensure that recommendations remain relevant and aligned with current employment opportunities. From a user experience perspective, future improvements may include interactive dashboards, visual analytics, and comparative analysis features that allow users to explore personality distributions and career paths more effectively.

In addition, future development will include multi-language support to improve accessibility for a diverse user base. The current system supports only English, which limits its usability among non-English-speaking populations. To address this, assessment questions will be translated into multiple languages such as Spanish, Mandarin, Hindi, and French, ensuring semantic accuracy and cultural relevance across translations. Moreover, the user interface will be localized to provide a seamless and intuitive experience for users in different linguistic regions.

Finally, incorporating natural language processing (NLP) techniques to analyze user-generated content, such as essays or feedback, could provide an additional layer of personality insight, leading to more comprehensive and accurate predictions.

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recommendation, several enhancements can be considered to further improve its accuracy, scalability, and practical applicability.

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