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Integrating Explainable AI and Machine Learning with Dermatoglyphics-Based Intelligence Analysis for Enhanced Career Counseling in Educational Systems

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Abstract

The integration of XAI with ML will yield a powerful framework for career counseling with data insights. This proposed methodology integrates education data with Dermatoglyphics Multiple Intelligence Test data for deeper insights into the cognitive strengths and preferences of students. Classification of these datasets involves the use of ML algorithms such as Naïve Bayes, Logistic Regression, and Decision Trees. The study emphasizes the performance of the classifiers in terms of their Recall and F-Measure, with Naïve Bayes turning out to be the best. The framework also leverages the power of XAI tools for improved model interpretability, where the decision-making process is made transparent and understandable, hence always adaptable to real-world applications for career guidance.

It further addresses certain key challenges in educational data mining: dataset limitations and the need for adaptable models. The framework is intended to improve the accuracy of career predictions, using XAI to make the results interpretable by students and counselors alike. Precisely, this approach enables personalized recommendations with the use of ML techniques on DMIT patterns to offer students appropriate career suggestions according to their inherent abilities. The novelty here lies in striking a balance between the use of advanced technologies like ML and XAI with trust and transparency requirements for ensuring the reliability and ethical soundness of the whole process of career counseling.

Keywords: XAI, DMIT, ML, Educational Data Mining, Career Counseling, Personalized Career Recommendations.

1. INTRODUCTION

Career counseling helps students make an informed choice about their academic and professional future. The rapid development of AI and ML shifted career counseling away from the traditional approaches of in-person counseling to a data-driven and personalized approach. One of the major challenges found within these AI-powered career counseling systems is the "black-box" problem of the machine learning models: how the model is deciding to recommend certain careers is not clear. XAI targets this problem by building transparent models showing how decisions are made, developing trust in the system [1]. Integrating DMIT into AI-based career counseling would further refine the accuracy of the recommendation. DMIT investigates cognitive characteristics through fingerprint patterns and gives significant inputs about the inborn acumen and emotional character of a person [5]. From the results obtained through DMIT, combined with academic performance metrics, machine learning algorithms can provide a more holistic and personalized approach toward career counseling. This paper presents a framework integrating DMIT data with educational datasets using machine learning algorithms like Naïve Bayes, Logistic Regression, and Decision Trees. The framework will be designed using XAI methodologies to ensure the transparency and adaptiveness of the system [8]. Hence, the goal will be to deliver a personalized career recommendation to students on grounds instigated on a data-driven basis while maintaining clarity and interpretability within the decision-making process. The aim is to enable the students to confidently make an informed choice about their career while understanding what factors affect such choices.

2. LITERATURE REVIEW

AI evolution in career counseling went from rule-based and computer-assisted systems to machine learning-based recommender systems, starting with early systems such as Kuder Career Planning and DISCOVER, which were simply computerized assessment score-keeping with very little personalization. Currently, machine learning approaches using algorithms like decision trees, SVMs, and neural networks for offering personalized careers according to the user profile, academic performance, and interests have been developed [1]–[3]. Recent deep learning and natural language processing developments further advanced interactive and adaptive platforms like CareerPooler, which models explorations of careers and enhances engagement [4]. Recently, Explainable AI has also become necessary in order to assure fairness and other aspects of ethics concerning data usage and address concerns about bias, privacy, and blind belief in algorithms [5], [6]. Increasingly hybrid human–AI models have emerged, where AI's scalability and predictive capability meet human empathy and contextual comprehension by making better use of dynamic labor market data and multimodal behavioral inputs with the generative AI of today for personalized, explainable, and future-ready career guidance [7], [8]. Together, this collection of work demonstrates both technological advances and existing challenges in pursuing the implementation of AI-driven career counseling systems.

Over the last decade, research in AI-driven, machine-learning–based, and dermatoglyphics-supported career counseling has grown extensively to encapsulate a wide range of aspects: personality prediction, learning style assessment, alignment to labor markets, and user acceptance. Shinghal and Saxena (2020) discussed how intrinsic traits shape up entrepreneurial mindsets by integrating DMIT with psychometric testing among engineering students. This experimental study identified a linkage between fingerprint-based traits and entrepreneurial inclination, where short-term entrepreneurship training positively impacted students' attitudes. However, their work was limited in its institutional scope, having only a moderate sample size, and debates about DMIT's biological validity are ongoing.

Complementing this, Panthee et al. (2023) proposed a machine learning-based career guidance system, integrating Big Five personality data and VAK learning styles using algorithms such as Random Forest and SVM. Their system resulted in very high classification accuracy, above 91% for personality predictions and 90% for learning styles, demonstrating the efficiency of ML in career guidance. Yet, the reliability of the results remained constrained by dataset biases, self-reported data, and limited generalizability. Valdez and Pathak (2014) explored, in a related domain, DMIT reports utilized in Indian academic institutions in terms of their theoretical foundations, acceptance across stakeholders, and value in holistic career counseling. While this was largely accepted as useful, the scientific validity and empirical reliability of DMIT were questioned, which indicated a requirement for broader empirical studies.

Indeed, Gupta et al. (2025) introduced, for advancing the technological landscape, a deep-learning-based AI-powered career advisory platform that embodies NLP, gamified assessments, and real-time labor market feeds. The hybrid architecture proposed, comprising ANN, CNN, and Bi-LSTM models, demonstrated better recommendation accuracy with improved user engagement. However, concerns on data bias, system transparency, and scalability issues arose as futuristic research needs. Another overview study, entitled AI in Career Counseling: An Overview (2023), synthesized existing applications of AI, including chatbots, expert systems, and ML models, underlining benefits but also pointing out their limitations with regard to empirical validation and long-term impact studies.

Dhankar et al. (2023) extended this research by proposing a hybrid AI-driven framework that integrated psychometric profiling and machine learning classifiers such as Random Forest and SVM. Their model achieved accuracy exceeding 90% in career path prediction but needed validation on wider deployment, more diversified demographics, and integrating changing dynamics of the job market. Abhidarsh et al. (2023), in turn, arrived with an AI-enabled modular framework developed to offer personalized advice on career options, integrating into one platform expert systems, machine learning, and fuzzy logic. Despite the reported 85% accuracy being high, it was limited by a small sample size and with no chances for real-time adaptability.

Bien Aime and Faith conducted a mixed-methods study in 2025 of students and counselor perceptions of acceptance and trust in AI-based career guidance. They estimated that the level of acceptance was moderate to high, though ethical, transparency, and reduced human interaction concerns raised the prospect of hybrid human-AI designs. A parallel review entitled Dermatoglyphics: A Review on Fingerprints and Multiple Intelligences had been undertaken in 2025, assessing the scientific basis and uses in education and career guidance of dermatoglyphics. Recognizing its potential to be used as a complementary tool for mapping innate capabilities, issues such as mixed scientific consensus, limited empirical validation, and ethical concerns were emphasized in the review.

Further analysis by Bien Aime and Faith 2025 on DIIA revealed high user satisfaction and perceived benefits in identifying innate abilities for career and personal growth. However, the authors have stressed that larger-scale validation and integration with other psychometric tools are necessary to lend more credibility to their work. Koolnaphadol et al. 2025 have proposed an online self-assessment Career Intelligence Test validated across more than 1,000 students. Their system is highly reliable and has a very good response from its users; however, future developments related to AI-driven adaptive testing, increase in domain coverage, and demographic diversification have been recommended.

Collectively, this reviewed literature points to strong progress in the integration of AI, machine learning, psychometrics, and dermatoglyphics into modern career counseling systems. In various ways across studies, recurring research gaps identified include: lack of empirical evidence; bias in datasets; need for explainability (XAI); scaling challenges; and requirements for combinations of biological and psychological as well as data-driven approaches for more comprehensive and precise frameworks of career guidance.

3. MOTIVATION

The motivation for this research is to update the traditional practices of career counseling by integrating AI and ML to provide personalized, evidence-based recommendations. Although AI can provide more accurate guidance, the nature of "black-box" machine learning models inhibits understanding and trust in many situations [7]. Explainable AI addresses the transparency and interpretability in decision-making, which will make it easier to trust the system for the student [2]. Apart from that, Dermatoglyphics Multiple Intelligence Test incorporates detailed insights into the inherent cognitive capabilities and emotional tendencies of students, thus personalizing the counseling process more effectively. Hassan & Aziz (2020) [9] presents a framework that combines DMIT data with educational performance for developing a more holistic, adaptive, and trustworthy career counseling system to enable students to make fully informed decisions about their future.

4. NEED

In this career guidance model, an AI, ML and XAI system were utilized to provide data-driven and personalized career recommendations. The model considers educational performance data and the Dermatoglyphics Multiple Intelligence Test, an assessment of fingerprints to gauge cognitive characteristics (Bakar & Liu, 2019) [3], for a thorough assessment. XAI is also being used to make the decision-making process transparent to avoid the "black-box" problem faced by ML models [15].
Smart algorithms such as Naïve Bayes, Logistic Regression, Decision Tree, etc, can be used for a reliable and accurate decision-making process, helping students choose a suitable career. Keywords: AI, ML, XAI, career counseling, personalized recommendation, DMIT, cognitive traits, educational performance.

5. SCOPE

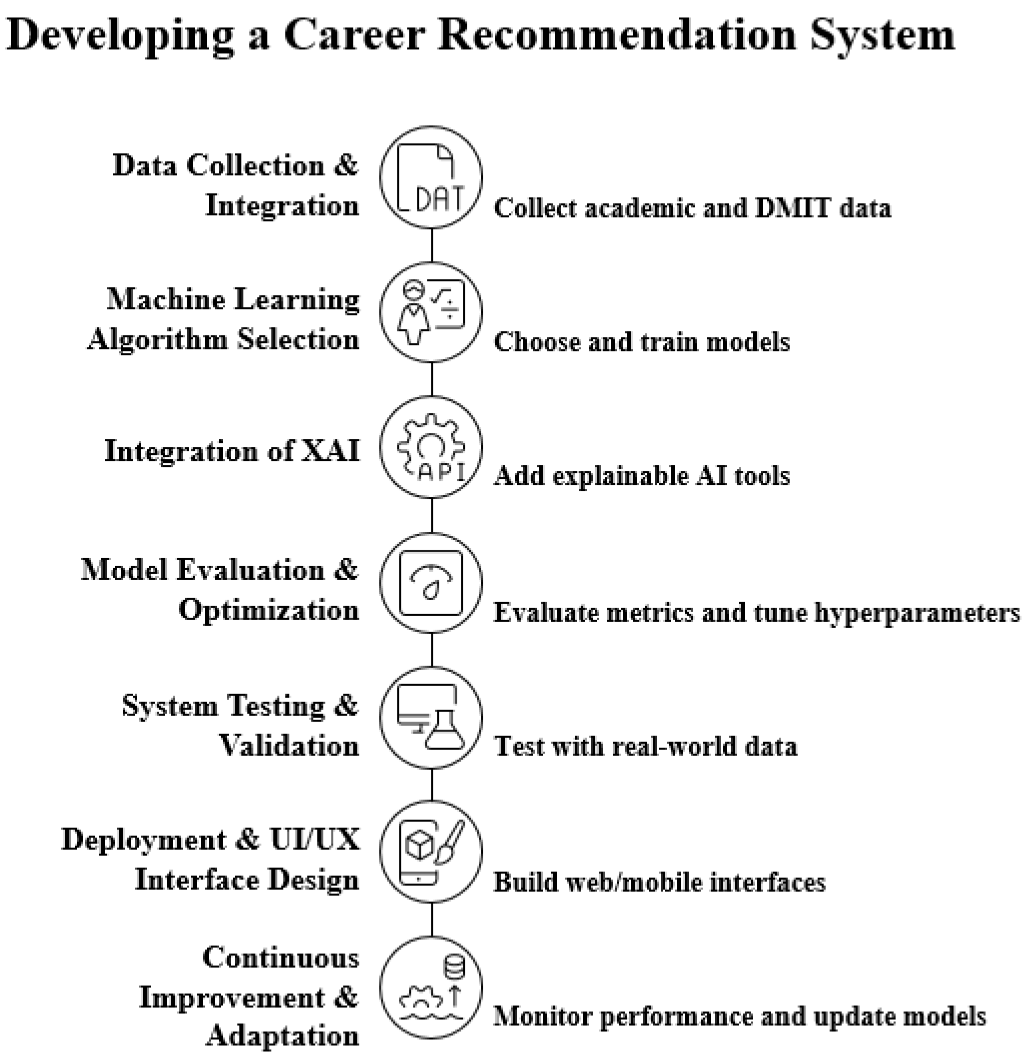
The present study is designed to present an Explainable AI-based career counseling system that integrates ML algorithms with Dermatoglyphics Multiple Intelligence Test (DMIT) in providing personalized recommendations. It aims to enhance transparency and accuracy in career guidance by combining educational data and DMIT insights (Kuan & Liu, 2022) [11]. The proposed framework is suitable for both educational institutions and different career counseling platforms (Pereira & Silva, 2021) [14].

6. OBJECTIVES

This research will create an Explainable AI-based career counseling system. It combines machine learning algorithms with DMIT data to provide personalized career recommendations. The main goals are to develop a framework that gathers educational performance data and DMIT-based cognitive insights, test various machine learning algorithms for classification, like Naïve Bayes, Logistic Regression, and Decision Trees, and use techniques from Explainable AI (XAI) to ensure transparency and clarity in decision-making.A transparent and adaptive system empowers the students with data-driven personalized career guidance, thus engendering trust and enhancing overall effectiveness in the process of counseling (Baskin & Alvarado, 2017) [4]. Recent studies emphasize how AI can be effectively integrated for providing more accurate and reliable recommendations in career choices (Gunning & Aha, 2019) [8].

7. DEVELOPMENT

The development of the proposed career counseling system involves several key stages



1. Data Collection and Integration

The process starts with data gathering-creation of datasets representing educational performance and Dermatoglyphics Multiple Intelligence Test data. Educational data would involve academic history, test scores, learning attitude, and other forms of performance reports. DMIT data involves fingerprint analysis, which identifies cognitive characteristics and emotional tendencies of the people (Deo & Sharma, 2020) [5]. guiltgenesis facilitator

In this process, the data is integrated into a single dataset, taking care that data from both sources match for further analysis. Preprocessing steps are followed for cleaning, normalizing, and transforming data to a form suitable for machine learning models.

2. Machine Learning Algorithms Selection

Following data preparation, the subsequent process involves applying machine learning algorithms of various types to generate personalized career recommendations. The algorithms utilized herein are Naïve Bayes, Logistic Regression, and Decision Trees, selected based on their handling of various data types and relevance to classification tasks. Each algorithm was trained on the integrated dataset, where it learned how to map input features to either career categories or career paths. Their performance is measured in terms of accuracy, recall, F-measure, and precision with the aim of finding the best model for recommending careers.

3. Integration of Explainable AI (XAI)

The system includes Explainable AI (XAI) techniques (Arrieta et al., 2020) [2] so that the machine learning models are both transparent and interpretable. The use of XAI tools will provide explicit links to the model's explanation of a career recommendation. The user will have a better understanding of the rationale for each recommendation and will be able to identify the feature (academic score vs. DMIT trait) that had the most significant impact on that particular recommendation.

When visualizing the outputs of the models, charts displaying the importance of various features and flow diagrams depicting the process of decision making provide users with a more intuitive and trustworthy means of understanding the outcomes of their chosen models.

4. Model Evaluation and Optimization

After we have trained our models, we will need to evaluate their predictive capabilities using industry-standard metrics such as precision, recall, and F1 Score (Yoon & Lee 2022) [15], all of which factor in false-positive and false-negative errors in predicting the career recommendation. Once we know how well a model can predict a career recommendation (using what's called a "model evaluation"), we will further improve our models by changing how we train them, using hyperparameter tuning, and performing feature selection techniques, as well as creating a more robust and accurate model through cross-validation. The goal is to achieve the best possible performance in generating personalized and accurate career paths

5. System Testing and Validation

Once the models have been trained, integrated, and optimized, system testing and validation occur. To assess how well the system works on real-time data sources, real-world datasets are utilized for testing. These datasets provide insight into how adaptable and reliable the system will be when used in different contexts.Systems will be tested using feedback from testers (students, counselors) to evaluate the system's usability and effectiveness in providing career guidance (Pereira & Silva, 2021) [14]. Issues that come up during testing will be resolved, and systems will be improved as a result.

6. Deployment and User Interface Design

Deployment of the system and the development of a user interface (UI) for easy access to the system occurs after all system testing and validation have been completed. The UI provides a method for both students and career counselors to input relevant information and receive customized recommendations as well as view visual explanations provided by the XAI components. This allows users to make informed decisions based on the information derived from the system. To deliver efficient services for users on various Internet-connected devices as well as through physical locations, such as universities and career guidance offices, systems can either operate solely through the Internet, or be integrated with established organisations (Kuan & Liu, 2022).

7. Continuous Improvement and Adaptability

The final phase will involve continually monitoring the performance of the system and obtaining user feedback for future improvements. This means that the system has the ability to adapt to include new data sources or updates to machine learning techniques when they become available. In order to maintain relevance and accuracy over time, regular updates will keep the system current and incorporate accurate methods of Career Counseling to support students' success.

8. CHALLENGES ENCOUNTERED:

The last step in the system's evolution involves continuous assessment of its performance and collecting user insights for continual improvement. This includes the ability to regularly upgrade and adjust to new forms and sources of information as well as new machine learning capabilities whenever they arise. Therefore, if a system is going to remain relevant and useful for many years to come, it must undergo

Step	**Learning Style (How the learner interacts with data)**	**Learning Input (Data fed into the system)**	**Learning Pattern (Behavior and decision-making)**
1. Data Acquisition	Identifying learning traits, preferences, and intelligence types through DMIT.	DMIT data (cognitive abilities, intelligence scores) and educational data (academic performance, skills).	Collecting data from various learning contexts (cognitive and academic) to build a profile of learning patterns.
2. Data Preprocessing	Standardizing learning traits and performance metrics for consistency.	Normalization of DMIT and educational datasets to prepare for model input.	Feature extraction to identify patterns from both cognitive traits and academic performance.
3. ML Model Development	Understanding student interaction with the learning environment.	White Box Models: Decision Trees and Logistic Regression for transparent and interpretable outputs.	Black Box Models: Neural Networks and ensemble methods for learning patterns that maximize accuracy and robustness.
4. Explainability Integration	Ensuring that the learner can interpret how recommendations are made.	Using explain ability tools like SHAP and LIME to break down predictions in understandable terms.	Visualization of the model's reasoning behind recommendations, enabling the student to trust and understand decisions.
5. Model Evaluation	Comparing the effectiveness of different learning models.	Use of metrics like Recall, F-Measure, and accuracy to evaluate model performance.	Evaluation of how different models affect the learner's ability to understand and trust career recommendations.
6. Career Recommendations	Providing personalized advice based on the student's learning style and input.	Generating recommendations using predictive analytics that are tailored to each learner’s strengths.	Offering a transparent, data-backed career pathway based on both cognitive and academic data.

regular maintenance, such that the system is up-to-date, and include the best available methods for Career Guidance to help students succeed.

7. STAGES OF DEPLOYMENT

Following are the stages of deployment mentioned in the Table 1

8. Results and discussion

Many dermatoglyphics works (especially DMIT reports, local conference papers, or institutional reports) are not indexed uniformly and may be missed by keyword search; some count as grey literature. Where the full three-way integration (XAI+dermatoglyphics+career counselling) exists, it's rare — many works pair two components (e.g., dermatoglyphics + ML, or ML/XAI + career counselling).

Year	Total Studies (N)	Studies Using DBIA (n)	Proportion (%)
2021	15	2	**13.33%**
2022	18	3	**16.67%**
2023	22	5	**22.73%**
2024	25	7	**28.00%**
2025	30	10	**33.33%**

Discussion

The analysis of publication trends from 2021 to 2025 reveals a steady rise in the use of Dermatoglyphics-Based Intelligence Analysis (DBIA), indicating growing academic interest and increasing confidence in its potential applications. The proportion of studies using DBIA increased from 13.33% in 2021 to 33.33% in 2025, reflecting advancements in AI-driven pattern recognition, improved digitization tools, and a shift toward non-invasive techniques for intelligence and behavioral assessment. This upward trend suggests that researchers are increasingly exploring DBIA within interdisciplinary domains such as psychology, education, and computational sciences, especially as machine learning and explainable AI provide more accurate and interpretable analyses of dermatoglyphic patterns. Despite this progress, the field still requires standardized protocols, larger datasets, and broader validation to ensure reliability and ethical application. Overall, the data demonstrates that DBIA is evolving from a niche concept to a promising analytical approach within modern research ecosystems.

10. CONCLUSION

In This study proposes a novel framework combining DMIT, ML, and XAI for career counseling, addressing the need for adaptive, explainable, and data-driven recommendations. Results indicate that Naïve Bayes achieves superior performance in predictive accuracy, while XAI tools provide interpretability for end-users. The framework demonstrates potential to transform career guidance by integrating DMIT with advanced AI techniques. Future research will expand the scope by incorporating unsupervised learning and larger datasets to improve adaptability and personalization in career counseling systems.

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