Semarak International Journal of Machine Learning

SEMARAK ILMU PUBLISHING

Journal homepage: https://semarakilmu.my/index.php/sijml/index
ISSN: 3030-5241

Artificial Intelligence (AI) Powered Algorithms and Model for Career Guidance System Development and Evaluation

Washington Entsie Sam[1,*], Alimatu Saadia Yussiff[1], Isaac Armah-Mensah[1], Wan Fatimah Wan Ahmad[2], Aaron Jon Tetteh[1], Andrews Ankomahene[1]

[1] Department of Computer Science and Information Technology, School of Physical Sciences, University of Cape Coast, Cape Coast, Ghana
[2] Department of Computer and Information Science, Universiti Teknologi PETRONAS, Seri Iskandar, Perak, Malaysia

ARTICLE INFO

Article history:
Received 4 July 2025
Received in revised form 13 August 2025
Accepted 20 September 2025
Available online 6 October 2025

Keywords:
Career Guidance, Artificial Intelligence (AI), Decision Tree, Model for Career Guidance System, Algorithms for Career Guidance System

ABSTRACT

Choosing a suitable career is one of the most critical decisions in an individual's life, yet increasing career options have made this process more challenging for students. About 40% of students are unsure about their career possibilities, per a survey by the Council of Scientific and Industrial Research (CSIR). This has resulted in the wrong career choice in a field that was not intended for them. To avoid the repercussions of making the wrong job choice, it is crucial to make the proper career option at the right age. The purpose of this research is to develop an Artificial Intelligence powered career guidance system to overcome traditional counseling limitations like lack of personalization and outdated methods to assist the students in selecting the suitable career path. The proposed system is a web application that integrates the Big Five Personality Traits model and Artificial Intelligence algorithms to provide tailored career recommendations based on users' skills, interests, and personality assessments. Six machine learning models were evaluated, with the Decision Tree achieving the best performance at 97% accuracy, along with high precision, recall, and F1-scores. Usability testing with 55 participants evaluated the system in real-world conditions, using the Questionnaire for Website Usability (QWU). The results showed a high user satisfaction of 81.8%, emphasizing the system's accessibility, ease of use, and effectiveness in providing personalized career recommendations. The results demonstrate the potential of AI-powered career guidance to assist users in making informed career decisions.

1. Introduction

In today's rapidly evolving world, career guidance has become increasingly important as students face a wide range of educational and occupational opportunities. Choosing a suitable career path is not only a critical decision in shaping one's future but also directly affects job satisfaction, employability, and long-term success. However, many students struggle to understand themselves, their interests, and their skills, which often hinders them from selecting appropriate fields of study

* *Corresponding author.*
E-mail address: washington.sam@ucc.edu.gh

https://doi.org/10.37934/sijml.7.1.917

or preparing for the job market. This lack of self-awareness frequently prevents them from exploring viable career alternatives and leads to poor decision-making.

Numerous studies have highlighted the challenges associated with ineffective career choices. According to a recent UNESCO poll involving 115,000 participants across 33 countries, about 60% of respondents, mostly young people, acknowledged selecting the wrong career path [1]. Such misguided decisions frequently result in job dissatisfaction, high university dropout rates, underemployment, and a mismatch between academic qualifications and job market needs. These issues underscore the urgent need for more effective career guidance approaches. Traditional career counseling emphasizes self-awareness and understanding one's abilities, but misconceptions often lead to regret in career choices [2]. For example, high-achieving science students may mistakenly choose chemical engineering, highlighting the inefficiencies of manual guidance. Although several countries have attempted to address this issue for instance, Finland's national career guidance strategy aligns individual skills and interests with job market opportunities to reduce dropouts, improve degree completion, and accelerate job market transitions [2] traditional systems remain limited in their scalability and adaptability. Similarly, computer-assisted career guidance (CACG) systems have shown promise in enhancing career decision-making self-efficacy, especially among secondary school students, but their effectiveness varies depending on career maturity and levels of autonomy [3].

In response to these limitations, researchers have proposed AI-powered career guidance systems that leverage machine learning algorithms, web applications, and career-related APIs to provide more dynamic and data-driven recommendations [4]. Career guidance is generally defined as the process of supporting individuals in understanding their interests, skills, and values to make informed educational and occupational choices [5]. While websites and applications have emerged to support this process, most rely narrowly on either personality traits or interests, producing inconsistent results and overlooking other vital attributes such as skills, proficiency levels, and academic achievements [6][7]. Furthermore, traditional counseling often depends on static questionnaires that fail to reflect student development, resulting in continued mismatches between qualifications and opportunities [1].

Artificial Intelligence (AI) offers a promising solution by transforming decision-making in career guidance, education, and employment through predictive analytics and personalization. Machine learning (ML) and natural language processing (NLP) enable intelligent systems to deliver adaptive, evidence-based recommendations that surpass the static nature of traditional counseling [8]. Among ML techniques, the Decision Tree algorithm stands out due to its interpretability and effectiveness in handling heterogeneous features such as skills, interests, and personality traits [9]. A robust AI-driven career guidance model involves integrating multiple classifiers, validating results with performance metrics such as accuracy, precision, recall, and error rates, and deploying user-friendly platforms that ensure accessibility across diverse student populations [10].

Algorithms form the backbone of these systems, driving personalized recommendations and intelligent decision-making. Early approaches employed rule-based systems and decision trees to map student attributes to career paths with high interpretability. Over time, clustering methods such as k-means and collaborative filtering uncovered hidden patterns and enabled career suggestions based on peer similarities [11]. More recently, advanced approaches incorporating support vector machines, neural networks, and NLP-powered conversational agents have emerged, enabling highly adaptive and interactive guidance aligned with dynamic labor market demands [12]. These developments demonstrate that AI systems can move beyond static, single-factor assessments to generate holistic, multi-dimensional recommendations.

Recent advancements in AI and ML create new opportunities to address the shortcomings of traditional and early digital approaches. By integrating diverse data sources such as personality traits, skills, academic performance, and interests. AI systems can deliver comprehensive, evidence-based career guidance [13]. Algorithms like Decision Trees, Random Forests, and Neural Networks can analyze large datasets to identify patterns and correlations among student attributes, enhancing both accuracy and adaptability [14]. Unlike personality or interest only platforms, these AI-powered systems consider a wide range of student characteristics to generate more reliable and personalized recommendations. Beyond suggesting career options, such systems can also highlight relevant skills, interest and labor job trends, equipping students with actionable insights for long-term planning [4].

Nevertheless, challenges remain. Many existing AI-driven career guidance systems fail to fully integrate diverse student attributes into a single framework or lack scalability for large-scale adoption. Moreover, limited real-time adaptability restricts their ability to adjust recommendations as students develop or as labor market conditions evolve. These gaps highlight the pressing need for a comprehensive AI-powered career guidance model that integrates multi-factor data, leverages adaptive algorithms, and delivers personalized, dynamic, and scalable recommendations to support students in making informed educational and career decisions.

1. Methodology

The methodological framework of this study is presented in Figure 1, The methodology consists of five key phases: data collection, pre-processing, feature engineering, model training, system implementation, and evaluation metrics as discussed in the sub section

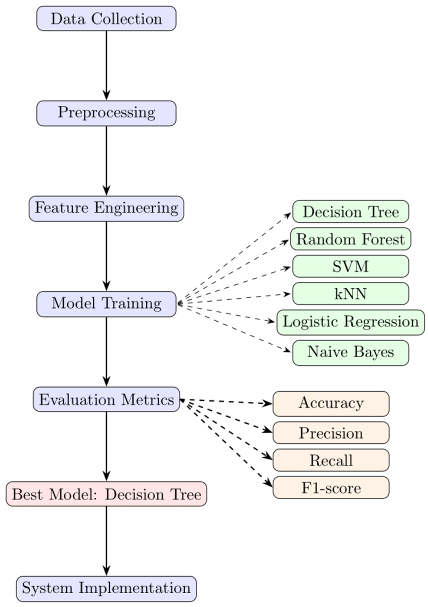

Fig. 1. Workflow of the proposed methodology from dataset to best system Implementation

1.1. Data Collection

The dataset used was secondary data, sourced from academic journals, government reports, and publicly available repositories such as Kaggle.com, data.world, and data.gov.gh. The initial dataset of 800 records was expanded to 3,000 to capture variations in skills and interests. In total, the dataset comprised over 3,000 unique rows with several features and a target variable.

1.2. Data Pre-processing

The dataset included five primary features: skills, interests, level of interest, level of skills, and assessment test scores. Since the data was originally categorical, rigorous pre-processing steps were applied, including removal of null and inconsistent values, error correction, and format standardization. Label encoding was then used to transform categorical variables into numerical values, ensuring compatibility with machine learning algorithms and enhancing feature expressiveness.

1.3. Feature Engineering

Pre-processed data was refined into a machine-readable format using feature engineering. This ensured that user attributes (test scores, skills, and interests) were transformed into high-quality model inputs.

1.4. Model Training and Validation

The dataset was split into 80% for training and 20% for testing, and k-fold cross-validation was applied to ensure reliable results. Six machine learning algorithms were compared: Decision Tree, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression, and Naïve Bayes. Their performance was evaluated using accuracy, precision, recall, and F1-score. The comparison helped identify the most suitable model for the AI-powered career guidance system.

1.5. Evaluation metrics

Numerous assessment indicators were used to evaluate the functionality and effectiveness of the developed career guidance models. These metrics provide quantifiable measures that demonstrate how well the models can predict suitable career recommendations for students. The performance metrics used in this study include confusion matrix.

2.5.1 confusion matrix,

The performance of the AI algorithms was evaluated using the Confusion Matrix which provide a comprehensive way to represent the result of AI algorithm. Figure 2 illustrates the comparison between the model’s predictions and the actual outcomes, presenting the findings across four distinct categories for clearer interpretation: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) as shown in fig 2. True positives (TP) are cases where the system correctly predicts a career as suitable. True negatives (TN) represent cases where the system accurately identifies a career as unsuitable. False positives (FP) occur when the system wrongly recommends a career as suitable, while false negatives (FN) happen when the system fails to recommend a career that is actually suitable.

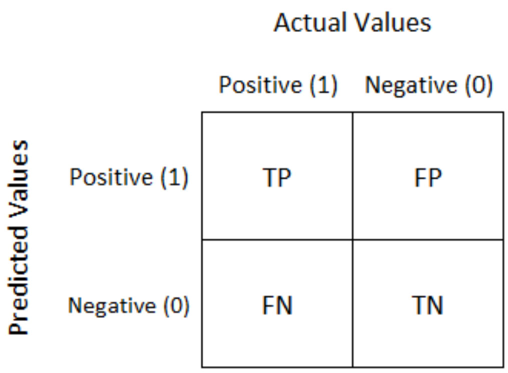

Fig. 2. Assessment Test Questions and subjective user input

1.6. System Design and Implementation

The system design and Implementation has been organized into four main components namely frontend, backend, database, and AI engine. **Frontend:** Implemented as a web application using HTML, CSS, and JavaScript. Users create accounts and then login to complete an Assessment Test (Big Five Personality traits), and input personal skills, level of skills, level of interest, and interests. The interface ensures integration of both objective (test scores) and subjective (user input) data as shown in figure 3 and 4.

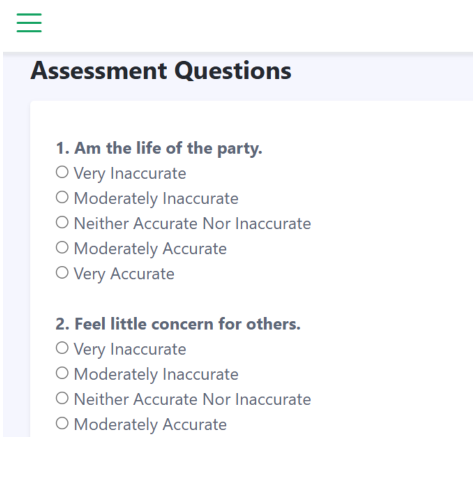

Fig. 3. Assessment Test Questions Interface

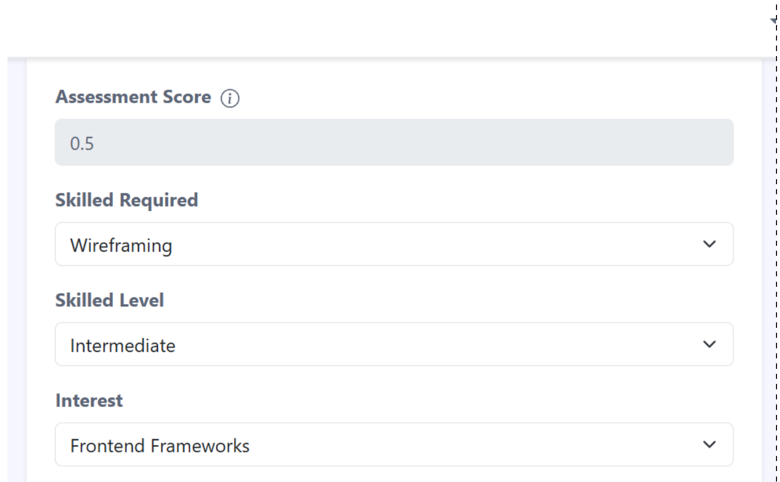

Fig. 4. subjective user input of skills, interest

Backend: Built using Flask and RESTful APIs, the backend manages communication between system components. It validates user inputs, handles authentication, manages sessions, and transfers data securely. It also forwards data to the AI engine and returns career recommendations to the frontend for visualization as shown in figure 5.

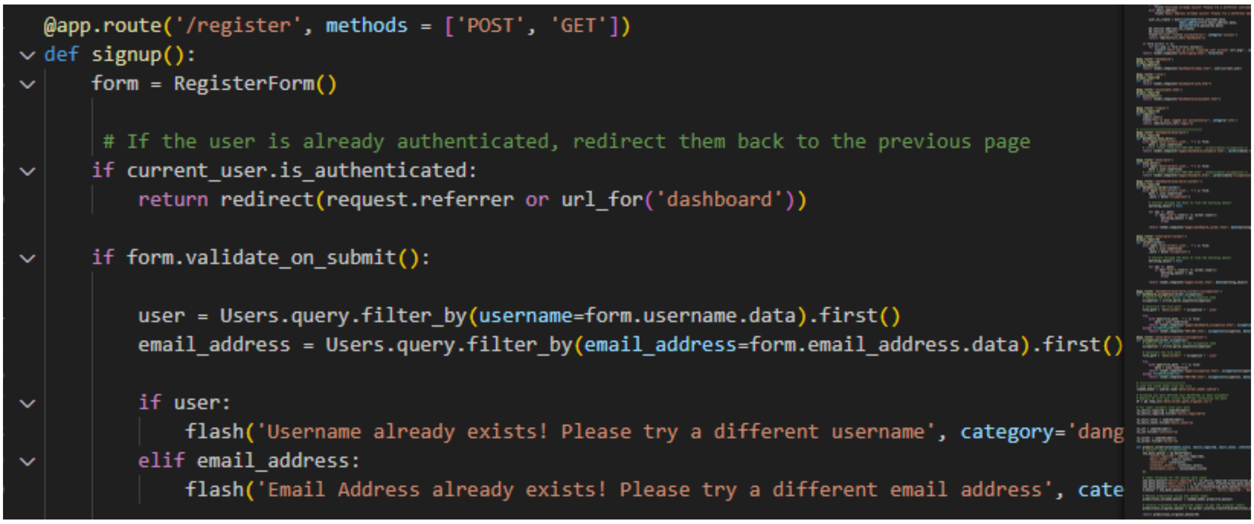

Fig. 5. Backend controller for signup

Database: Stores user profiles, test results, skills, interest levels, and historical recommendations. It also maintains external career-related datasets, which serve both real-time recommendation generation and AI model training. SQLite was used for implementation, supporting both structured and semi-structured data as shown in figure 6

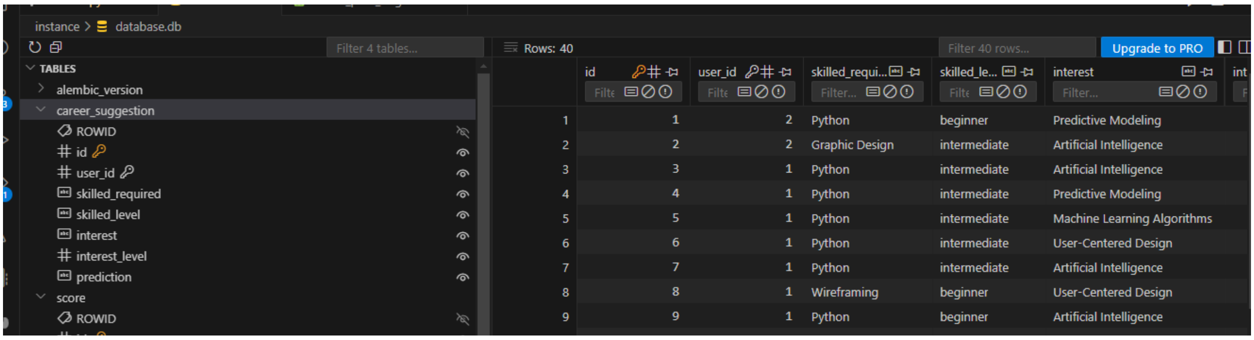

Fig. 6. Database Structure of the system

AI Engine: The decision-making core of the system, consisting of Feature Engineering and the Recommendation Engine. Feature Engineering prepares data for analysis, while the Recommendation Engine (Decision Tree-based) predicts suitable careers based on user profiles. Continuous retraining ensures model adaptability to emerging trends.

2. Results and Discussions

Six AI classifiers were evaluated on the dataset to predict suitable career paths for students. The performance of the different models is presented in Table 1 and figure 7. Among them, the Decision Tree classifier achieved the highest performance across all metrics, with an accuracy score of 0.97, making it the best-performing model. This was followed by the Random Forest and k-Nearest Neighbors models, with accuracies of 0.90 and 0.86, respectively. The Naïve Bayes classifier obtained an accuracy of 0.78, while Logistic Regression and Support Vector Machine (SVM) both recorded the lowest performance, with scores of 0.62 each. The Decision Tree's superior results highlight its ability to capture complex relationships between test score, skills, level of skills and interest, and interests, more effectively than the other models

Table 1
Performance Measures for each of The Model

Models	Accuracy	precision	Recall	F1-score
Decision Tree	0.97	0.97	0.97	0.97
Random Forest	0.90	0.90	0.90	0.90
SVM	0.62	0.55	0.62	0.54
kNN	0.86	0.86	0.86	0.86
Logistic Regression	0.62	0.67	0.62	0.60
Naive Bayes	0.78	0.78	0.78	0.78

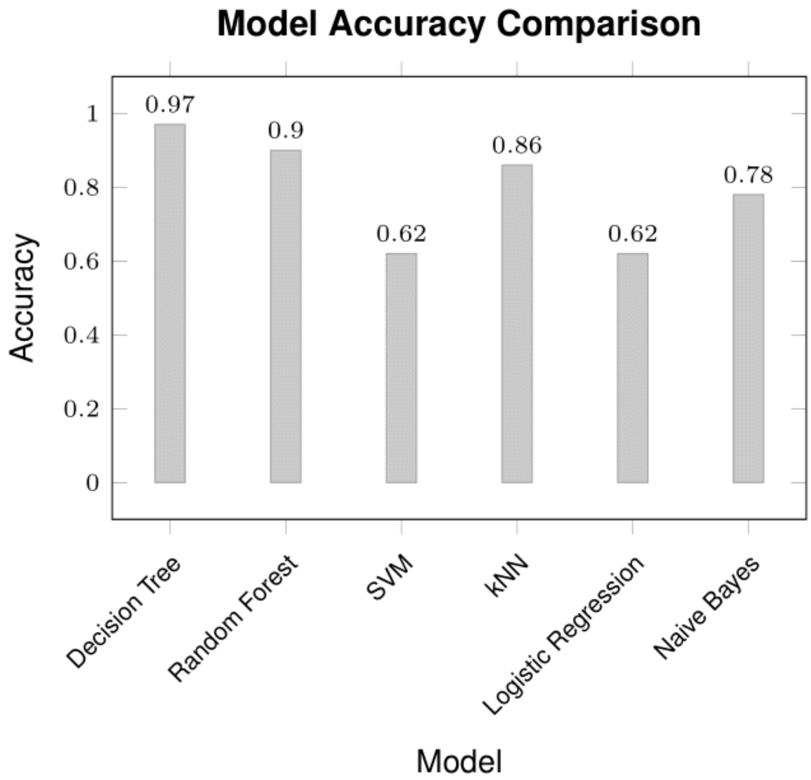

Fig. 7. Accuracy performance for each of the model

The system was also tested with manually entered data, which confirmed the Decision Tree's consistency, reliability, and high predictive accuracy. The results validate its suitability for deployment in the AI-powered career guidance system. The system was further evaluated through usability testing with 55 participants who registered on the application, completed the personality test, and provided their skills, interests, and levels of interest and skill. Based on this input, each participant received career recommendations generated by the AI model. Table 2 presents the distribution results, which reflect the effectiveness of the system in delivering accurate and relevant career guidance.

Table 2
Distribution of Ratings for Effectiveness

Rating (1-5)	Number of Responses	Percentage
1	0	0.0%
2	0	0.0%
3	0	0.0%
4	10	18.2%
5	45	81.8%

The results clearly show strong user satisfaction, with 100% of participants rating the system as either 4 or 5, and no participants reporting low or neutral ratings. A large majority (81.8%) rated the system with the highest score, indicating that the recommendations were perceived as both highly accurate and relevant to their career aspirations. The 18.2% who gave a score of 4 still demonstrated positive satisfaction, suggesting only minor areas for improvement, such as refining recommendation explanations or enhancing the interface for better user experience.

The snapshot of the intelligent career guidance system shown here presents the final results for the relevant test scenarios outlined in the preceding discussion. The figure 8 also highlights the accuracy and consistency of the model's predictions, demonstrating its effectiveness in providing reliable guidance to users

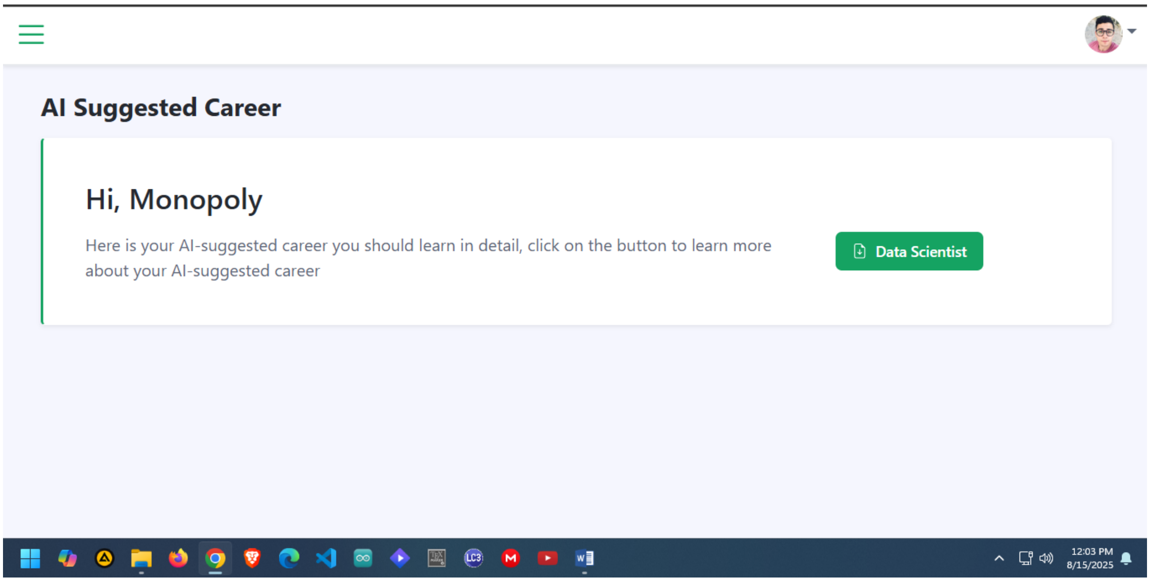

Fig. 8. Final Result using the application

3. Conclusion

This study evaluated six machine learning algorithms on a dataset of over 3,000 instances with five key features (skills, interests, levels of skills, levels of interests, and assessment scores), using an 80% for training and 20% testing. The Decision Tree outperformed all models with 97% accuracy, followed by Random Forest (90%) and k-Nearest Neighbors (86%), while Naïve Bayes, Logistic Regression, and SVM showed lower performance (62%). Further analysis using precision, recall, specificity, and F1-score confirmed the Decision Tree's robustness. Usability testing with 50 participants validated the system's practicality, as users successfully registered, completed assessments, and received reliable recommendations. This study makes the following contributions:

(i) **Integration of Multi-Factor Attributes**: a career guidance framework that incorporates interests, skills, academic performance, and personality traits, moving beyond traditional personality- or interest-only models; (ii) **AI-Powered Recommendation System**: a web-based platform leveraging Machine Learning techniques (Decision Trees, Random Forest, and Neural Networks) to provide accurate and adaptive career recommendations; and (iii) **User-Centric Accessibility**: a free, user-friendly online system accessible anytime, supporting students across diverse educational levels and backgrounds. Overall, the findings demonstrate that Decision Tree–based approaches can significantly enhance career guidance by integrating multiple factors, while future improvements could involve adaptive deep learning, hybrid ensemble methods, early integration in schools, and mobile deployment for broader accessibility.

Acknowledgement
This research was not funded by any grant.

References

[1] N. Pordelan and S. Hosseinian, "Design and development of the online career counselling: a tool for better career decision-making," *https://doi.org/10.1080/0144929X.2020.1795262* , vol. 41, no. 1, pp. 118–138, 2020, doi: 10.1080/0144929X.2020.1795262.
[2] A. Toni and R. Vuorinen, "Lifelong guidance in Finland: Key policies and practices," in *Career and career guidance in the Nordic countries*, Brill, 2020, pp. 127–143.
[3] H. Shimomura, "Computer-assisted career guidance and career decision-making self-efficacy," *Japanese Journal of Educational Psychology*, vol. 55, no. 2, pp. 276–286, 2007, doi: 10.5926/JJEP1953.55.2_276.
[4] S. Westman and A. Mononen, "Artificial Intelligence for Career Guidance-Current Requirements and Prospects for the Future," *IAFOR Journal of Education: Technology in Education*, vol. 9, p. 43, 2021.
[5] A. G. Watts, "Career development and public policy," *J Employ Couns*, vol. 37, no. 2, pp. 62–75, 2000.
[6] R. G. Sultana, "Review of national career development support systems in the Western Balkans," 2022.
[7] V. C. Müller and N. Bostrom, "Future progress in artificial intelligence: A survey of expert opinion," *Fundamental issues of artificial intelligence*, pp. 555–572, 2016.
[8] A. Rai *et al.*, "Phosphorylated EGFR (pEGFR T693) as a novel predictor of recurrence in non-functioning pituitary adenomas," *Front Endocrinol (Lausanne)*, vol. 12, p. 708111, 2021.
[9] S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Trans Syst Man Cybern*, vol. 21, no. 3, pp. 660–674, 1991.
[10] B. A. Mukhola, A. C. Kirui, and L. W. Kivuti-Bitok, "Perception and Practice of Kangaroo Mother Care Among Mothers of Pre-term Babies at a National Referral Hospital in a Limited Resource Setting," *East Afr Health Res J*, vol. 8, no. 1, p. 67, 2024.
[11] K. Reddy, M. A. Reddy, V. Kaur, and G. Kaur, "Career guidance system using ensemble learning," *Akhila and Kaur, Veerpal and Kaur, Gagandeep, Career Guidance System Using Ensemble Learning (July 14, 2022)*, 2022.
[12] N. Zhou, H. Cao, S. Wang, X. Li, and Y. Liang, "Parental career expectation predicts adolescent career development through career-related parenting practice: Transactional dynamics across high school years," *J Career Assess*, vol. 32, no. 1, pp. 125–141, 2024.
[13] M. A. Boden, *AI: Its nature and future*. Oxford University Press, 2016.
[14] K. S. Roy, K. Roopkanth, V. Uday Teja, V. Bhavana, and J. Priyanka, "Student Career Prediction Using Advanced Machine Learning Techniques," 2018. [Online]. Available: www.sciencepubco.com/index.php/IJET