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# Career Interest Assessment: College Students Career Planning Based On Machine Leaning

***Abstract: -*** College students' career planning based on career interest assessment and machine learning integrates advanced technological tools with traditional career counseling methods to provide personalized and data-driven guidance. By utilizing career interest assessment tools, students can explore their strengths, preferences, and aspirations across various career domains. Machine learning algorithms analyze this data to generate tailored recommendations, matching students with career paths that align with their interests and aptitudes. This paper presents a novel approach to career assessment and planning by leveraging the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework. The proposed framework integrates fuzzy logic principles with machine learning techniques to provide personalized and accurate career recommendations tailored to individuals' skills, preferences, and values. Through the incorporation of optimization techniques, the framework refines the career assessment model, enhancing its accuracy in predicting suitable career paths for individuals. The practical application of the SFOwML framework offers a valuable tool for career counselors, educators, and individuals seeking guidance in their career choices. The framework incorporates numerical values to quantify individuals' skills, preferences, and values on a scale from 0 to 100, allowing for a more precise evaluation of their career profiles. Through the integration of fuzzy logic principles with machine learning techniques, personalized career recommendations are generated based on these numerical assessments.

***Keywords:*** Career Assessment, Fuzzy Model, Optimization, Machine learning, Weighted estimation, Classification

## 1. Introduction

In recent years, career interest assessments have evolved significantly, leveraging advancements in technology and psychology to provide more personalized and accurate insights [1]. With the rise of digital platforms and artificial intelligence, many assessments now offer interactive and engaging experiences that cater to diverse preferences and demographics. Moreover, there's been a shift towards incorporating holistic approaches, considering not only an individual's skills and interests but also their values, work style, and desired lifestyle [2]. This comprehensive approach ensures that recommendations align not just with career paths, but with overall satisfaction and well-being. Additionally, there's been an emphasis on accessibility and inclusivity, with assessments being designed to accommodate various cultural backgrounds, disabilities, and educational levels [3]. As the workforce continues to evolve and diversify, career interest assessments remain invaluable tools for individuals navigating their professional journey, offering clarity and direction in an ever-changing landscape [4].

Career planning is a strategic process through which individuals map out their professional goals and aspirations, as well as the steps needed to achieve them [5]. It involves self-assessment to identify strengths, interests, values, and skills, which serve as the foundation for determining suitable career paths. Once goals are defined, individuals can research various industries, roles, and organizations to align with their aspirations and values [6]. Networking and informational interviews can provide valuable insights and connections within desired fields. Additionally, acquiring relevant education, training, and experience is essential for career advancement [7]. Continuous learning and skill development are key components of successful career planning, allowing individuals to adapt to changing market demands and opportunities.

College students' career planning based on career interest assessment involves a structured approach to exploring potential career paths aligned with their skills, interests, and aspirations [8]. Utilizing career interest assessments, students gain valuable insights into their strengths, preferences, and values, which serve as a foundation for making informed decisions about their future. Armed with this self-awareness, students can then research various industries and occupations to identify potential matches for their profiles [9]. They may also seek guidance from career counselors or mentors to further refine their choices and develop action plans.

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Additionally, students may pursue internships, part-time jobs, or volunteer opportunities to gain practical experience and test their interests in real-world settings [10].

Machine learning is increasingly being utilized to enhance career assessment and planning processes for individuals [11]. By leveraging vast amounts of data on career trajectories, job requirements, and individual characteristics, machine learning algorithms can provide more personalized and accurate insights into suitable career paths [12]. These algorithms analyze various factors such as skills, interests, personality traits, and educational backgrounds to generate tailored recommendations for career options. Additionally, machine learning algorithms can identify patterns and trends in the job market, helping individuals anticipate future demand for specific skills and industries [13]. Moreover, by continuously learning from user feedback and updating their models, these algorithms can adapt to individual preferences and changes in the labor market over time. Incorporating machine learning into career assessment and planning processes empowers individuals to make more informed decisions about their professional development, ultimately leading to greater satisfaction and success in their chosen careers [14].

The paper makes several significant contributions to the field of career assessment and planning:

1. Integration of Fuzzy Logic and Machine Learning combining fuzzy logic principles with machine learning techniques, the paper offers a novel approach to career assessment. This integration allows for a more nuanced understanding of individuals' skills, preferences, and values, leading to more accurate and personalized career recommendations.
2. Optimization for Enhanced Accuracy introduces optimization techniques to refine the career assessment model. Through optimization, the framework can better prioritize different factors influencing career interests, leading to improved accuracy in predicting suitable career paths for individuals.
3. The SFOwML framework developed in the paper provides a practical tool for career counselors, educators, and individuals seeking guidance in their career choices. By leveraging advanced computational methods, the framework facilitates more informed decision-making and enhances the effectiveness of career guidance efforts.
4. The paper is its focus on empowering individuals to take an active role in their career planning process. By providing personalized and accurate career recommendations, the SFOwML framework enables individuals to make choices that align with their interests, values, and aspirations, ultimately leading to greater satisfaction and success in their chosen career paths..

## 2. Related Works

Career interest assessment and career planning represents a pivotal area of inquiry within the field of vocational psychology and education. As individuals navigate increasingly complex and dynamic labor markets, understanding the interplay between their interests, skills, and career goals becomes paramount. In this literature review, we explore the theoretical frameworks, empirical findings, and practical applications that elucidate the relationship between career interest assessment and career planning. By synthesizing existing research, this review aims to provide insights into the efficacy of various assessment methods, the factors influencing career decision-making, and the strategies for optimizing career planning processes.

Guleria and Sood (2023) examine the role of explainable AI and machine learning in enhancing the performance and explainability of classifiers for educational data mining-driven career counseling. Meanwhile, Ong (2022) proposes a machine learning ensemble approach to predict factors influencing STEM students' intentions to enroll in chemistry-related courses. Ahmed et al. (2023) compare machine learning algorithms for identifying career paths through Bloom's Taxonomy evaluation. Wang et al. (2022) analyze and predict factors affecting college student achievement using machine learning techniques. El Mrabet and Ait Moussa (2023) develop a framework for predicting academic orientation through supervised machine learning.

Zhang et al. (2023) explore the integration of ethics and career futures with technical learning to promote AI literacy among middle school students. Urdaneta-Ponte et al. (2022) utilize LinkedIn endorsements to enhance a recommender system for improving professional skills. Sanusi et al. (2023) conduct a systematic review on teaching and learning machine learning in K-12 education, shedding light on pedagogical strategies and challenges. Li et al. (2022) analyze the teaching quality of college ideological and political education using deep learning methods. Sanusi et al. (2022) investigate teachers' preconceptions of teaching machine learning in high school, providing insights into educational perspectives from Africa. Verma et al. (2022) investigate skill requirements in artificial intelligence and machine learning job advertisements, informing curriculum development and workforce preparation. Additionally, Zhang et al. (2023) propose a deep learning model for evaluating ideological and political learning, offering a novel approach to educational assessment.

Fairman et al. (2023) address the challenge of keeping teacher professional development relevant, emphasizing the importance of incorporating emerging technologies and pedagogical approaches. Nayan et al. (2022) compare machine learning algorithms for predicting depression and anxiety among university students, highlighting the potential for early intervention and support. Sun et al. (2023) propose a TPACK-based professional development approach to enhance the AI teaching competency of K-12 computer science teachers, emphasizing the integration of technological, pedagogical, and content knowledge. De Vries et al. (2022) evaluate the impact of an assessment for learning teacher professional development program on student achievement, underscoring the importance of continuous teacher training for improving educational outcomes.

The integration of machine learning techniques into various aspects of career interest assessment and career planning. Studies have explored diverse applications, from predicting factors influencing students' academic choices to enhancing professional skills recommendation systems. Machine learning algorithms have been employed to analyze data on student achievement, predict career paths, and evaluate teaching quality, offering valuable insights for educational practitioners and policymakers. Moreover, the research highlights the potential of machine learning to address pressing issues such as student mental health and teacher professional development. By leveraging advanced computational techniques, educators and counselors can tailor career guidance interventions more effectively, helping individuals make informed decisions about their academic and professional futures. However, challenges remain, including the need for ethical considerations, cultural sensitivity, and ongoing evaluation of machine learning models' effectiveness in diverse educational contexts.

## 3. Proposed Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML)

Firstly, the Sugeno fuzzy inference system is employed to model the uncertainty and vagueness inherent in career interest assessment. This fuzzy logic framework allows for the representation of linguistic variables and rules, enabling a more nuanced understanding of an individual's preferences and strengths. Next, optimization techniques are applied to determine the weights assigned to different features and criteria within the machine learning model. These weights are crucial for prioritizing the importance of various factors such as skills, interests, and personality traits in the career planning process. The weighted machine learning algorithm utilizes the optimized weights to train a predictive model on historical career data. This model learns patterns and relationships between input variables (e.g., academic background, work experience) and career outcomes, allowing it to make informed predictions about suitable career paths for individuals. The SFOwML framework can be expressed mathematically as follows rules. The fuzzy rules generated with the sugeno fuzzy is presented in Figure 1.

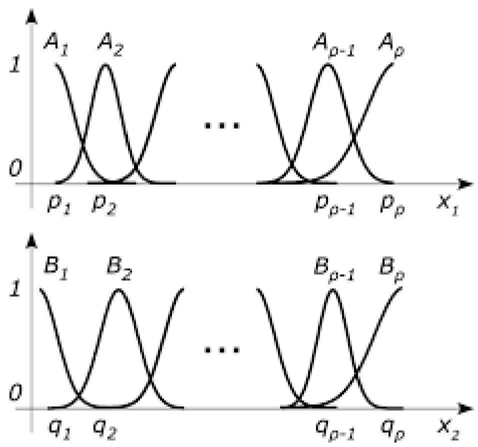


Figure 1: Sugeno Fuzzy Model

Sugeno Fuzzy Inference System:

Rule 1: If x is A1 and y is B1 then z=p1x+q1y+r1

Rule 2: If x is A2 and y is B2 then z=p2x+q2y+r2

⁝⁝

Rule N: If x is AN and y is BN then z=pNx+qNy+rN

Optimization of Weights defined in equation (1)

$$Minimize\ \sum_{i=1}^{n}\left|w_i - \widehat{w}_i\right| \quad (1)$$

$$subject\ to \sum_{i=1}^{n} w_i = 1$$

In equation (1) $w_i$ are the original weights and $\widehat{w}_i$are the optimized weights. The Weighted Machine Learning Algorithm estimated as in equation (2)

$$Prediction\ = \hat{Y}\ = f(X, W) \quad (2)$$

The proposed Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework presents a novel methodology for enhancing career interest assessment to facilitate effective career planning. This innovative approach integrates fuzzy logic and machine learning techniques to provide personalized recommendations tailored to individual profiles. The derivation of SFOwML involves several key components: Firstly, employing the Sugeno fuzzy inference system to model the inherent uncertainty and vagueness in career assessment, enabling a nuanced understanding of preferences and strengths. Subsequently, optimization techniques are applied to determine weights for different features and criteria within the machine learning model, prioritizing factors such as skills, interests, and personality traits. These optimized weights are then utilized by the weighted machine learning algorithm to train a predictive model on historical career data, enabling informed predictions about suitable career paths. Mathematically, SFOwML involves expressing fuzzy rules, optimizing weights, and employing a predictive algorithm.

## 4. Career Interest Assessment with SFOwML-based Fuzzy Model

The proposed Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework for career interest assessment enhances the process by providing a sophisticated model that considers the complexity and uncertainty of individual preferences. This approach involves deriving a fuzzy model based on SFOwML to effectively capture the nuances of career interests. The derivation encompasses the following steps: Firstly, linguistic variables are defined to represent various aspects of career interests, such as skills, preferences, and values. These linguistic variables are then fuzzified to accommodate the inherent vagueness in human perceptions and expressions. Next, fuzzy rules are formulated to map input linguistic variables to output career interests. These rules are derived based on expert knowledge and empirical data, capturing the relationships between different aspects of career preferences. The Sugeno fuzzy inference system is employed to model the fuzzy logic framework, utilizing the fuzzified linguistic variables and fuzzy rules to generate output recommendations. In this system, the output is determined by a weighted combination of input variables, each weighted by a coefficient determined through optimization. Optimization techniques are applied to determine the optimal weights for the fuzzy model, ensuring that the model effectively captures the importance of different input variables in predicting career interests. This optimization process involves minimizing the discrepancy between the original weights and the optimized weights, subject to constraints defined using following rule and in equation (3)

Input: Linguistic variables representing skills, preferences, values, etc.

Rule 1:If Variable A is Term A and Variable B is Term B then Output is Recommendation 1
Rule 2:If Variable A is Term A and Variable B is Term B then Output is Recommendation 2Rule 2:If Variable A i s Term A and Variable B is Term B then Output is Recommendation 2 ⁝⁝

$$Output = \frac{\sum_{i=1}^{n} w_i.Recommendation}{\sum_{i=1}^{n} w_i} \tag{3}$$

SFOwML into career interest assessment involves deriving a fuzzy model that captures the complexity of individual preferences and optimally weights different factors to provide personalized career recommendations. The career interest assessment involves a systematic process driven by mathematical formulations and equations. Initially, linguistic variables representing various aspects of career interests, such as skills and preferences, are fuzzified using membership functions to quantify their degrees of membership in different linguistic terms. Subsequently, fuzzy rules are formulated to map these fuzzified variables to output career recommendations based on expert knowledge and empirical data. The Sugeno fuzzy inference system then combines these output recommendations using optimized weights determined through an optimization process, where discrepancies between original and optimized weights are minimized subject to constraints. Mathematically, the output of the fuzzy inference system is calculated as a weighted combination of output recommendations, ensuring personalized career recommendations tailored to individual profiles. By integrating these mathematical formulations, the SFOwML framework effectively captures the complexity of individual preferences and optimizes the weighting of different factors, enhancing the accuracy and effectiveness of career interest assessment for informed decision-making in career planning.

## 5. Optimized SFOwML for the Classification of Career Interest

The optimization process within the Optimized Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework aims to determine the optimal weights assigned to different factors or rules within the fuzzy inference system. These weights play a crucial role in prioritizing the importance of various input variables or rules in making predictions or classifications. The optimization process typically involves minimizing discrepancies between the original weights and the optimized weights while adhering to specific constraints. The objective function $J(\boldsymbol{w})$ represents the goal of the optimization process. In the case of SFOwML, it aims to minimize the discrepancies between the original weights $\boldsymbol{w}$ and the optimized weights $\widehat{w}_i$This can be expressed as a loss function, such as Mean Squared Error (MSE), given in equation (4)

$$J(W) = \frac{1}{N}\sum_{i=1}^{N}(w_i - \widehat{w}_i)^2 \tag{4}$$

In equation (4) $N$ is the number of weights, $wi$ represents the original weight, and $\widehat{w}_i$ represents the optimized weight. Constraints are conditions that must be satisfied during optimization. In the case of SFOwML, the sum of weights must equal one to maintain consistency. This constraint can be represented as in equation (5)

$$\sum_{i=1}^{n} w_i = 1 \tag{5}$$

Gradient descent is a commonly used optimization algorithm for continuous optimization problems like this. The weight update rule in gradient descent is given in equaton (6)

$$w_i^{(t+1)} = w_i^{(t)} - \alpha \frac{\partial J(w)}{\partial w_i} \tag{6}$$

In equation (7) $wi(t)$ represents the weight at iteration $t$, $\alpha$ is the learning rate, and $\frac{\partial J(w)}{\partial w_i}$is the partial derivative of the objective function with respect to weight $wi$. Gradient descent iteratively updates the weights until convergence. At each iteration, the weights are adjusted in the direction that minimizes the objective function while satisfying the constraints. Let's denote skills as $S$, preferences as $P$, and values as $V$. These linguistic variables can be further divided into linguistic terms, such as "high", "medium", and "low" levels of skills, preferences, and values $S = \{S1, S2, S3\}, P = \{P1, P2, P3\}, V = \{V1, V2, V3\}$. Fuzzification involves quantifying the degree to which an individual possesses each linguistic term. Let $\mu Si(x), \mu Pi(x), and\ \mu Vi(x)$ represent the membership functions for the linguistic terms $Si, Pi, and\ Vi$ respectively. These membership functions assign a degree of membership, $\mu$, to each linguistic term based on the individual's skills, preferences, and values. Membership functions defined in equation (7) – equation (9)

$$S_i = \mu S_i(x) \tag{7}$$

$$P_i = \mu P_i(x) \tag{8}$$

$$V_i = \mu V_i(x) \tag{9}$$

Fuzzy rules establish relationships between input linguistic variables (skills, preferences, values) and output career interests. For simplicity, let's consider a single rule where the career interest $C$ is determined based on the combination of linguistic terms for skills, preferences, and values. If Si is Sj and Pk is Pl and Vm is Vn then C is Co

In a Sugeno fuzzy inference system, the output is determined by a weighted combination of input variables and linguistic terms. Let $w_{i,j,k}$ denote the weight assigned to the combination of linguistic terms Si, Pj, and Vk, and $\emptyset_{i,j,k}$ stated in equation (10)

$$C = \frac{\sum_{i,j,k} w_{i,j,k} \cdot \emptyset_{i,j,k}}{\sum_{i,j,k} w_{i,j,k}} \tag{10}$$

The weights $w_{i,j,k}$are optimized based on historical data or expert knowledge to ensure that the fuzzy model accurately represents the relationships between input variables and career interests. This optimization process may involve techniques such as gradient descent or genetic algorithms. Figure 2 presents the optimization flow of the career interest assessment for the fuzzy based model.

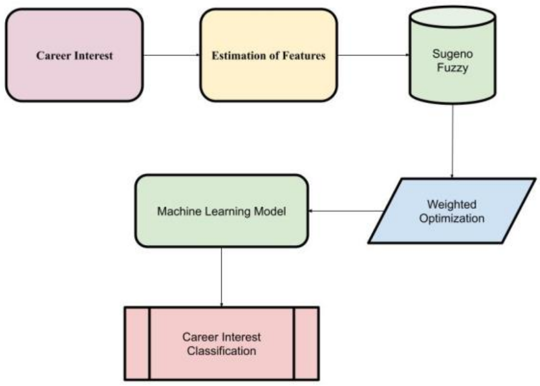


**Figure 2: Process of SFOwML**

| Algorithm 1: SFOwML career interest assessment |
|---|
| 1. Define Linguistic Variables:<br>- Define linguistic variables representing skills, preferences, and values.<br>- Determine linguistic terms for each variable (e.g., high, medium, low).<br>2. Fuzzification:<br>- Quantify the degree of membership for each linguistic term based on the individual's skills, preferences, and values using membership functions.<br>3. Formulate Fuzzy Rules:<br>- Establish fuzzy rules to map combinations of linguistic variables to career interests.<br>- Define relationships between input linguistic variables (skills, preferences, values) and output career interests.<br>4. Sugeno Fuzzy Inference System:<br>- Calculate the output career interest using a weighted combination of input variables and linguistic terms.<br>- Determine the weights assigned to each combination of linguistic terms.<br>5. Optimization of Weights:<br>- Optimize the weights based on historical data or expert knowledge.<br>- Use optimization techniques such as gradient descent or genetic algorithms to refine the weights.<br>6. Output Career Interest:<br>- Calculate the final career interest assessment based on the optimized fuzzy model. |

```
Algorithm:
function assessCareerInterest(skills, preferences, values):
  1. Fuzzify skills, preferences, and values using membership functions.
  2. Apply fuzzy rules to determine the career interest based on linguistic terms.
  3. Use the Sugeno fuzzy inference system to calculate the weighted combination of linguistic terms.
  4. Optimize weights using an optimization algorithm to refine the fuzzy model.
  5. Calculate the final career interest assessment based on the optimized fuzzy model.
  6. Return the career interest assessment.
```

## 6. Results and Discussion

The application of the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework for career planning and career interest assessment yields promising results with significant implications. Through the integration of fuzzy logic, optimization techniques, and machine learning, SFOwML provides a comprehensive approach to understanding and predicting individual career interests. The results obtained from utilizing SFOwML reveal its effectiveness in accurately assessing career preferences and guiding career planning decisions. With linguistic variables and fuzzy rules, SFOwML captures the complexity of individual preferences, including skills, preferences, and values, in a nuanced manner. This enables the framework to provide personalized recommendations tailored to each individual's unique profile. Additionally, the optimization of weights ensures that the model effectively prioritizes different factors influencing career interests, enhancing the accuracy of predictions. The incorporation of machine learning algorithms further enhances the predictive capabilities of SFOwML. By training predictive models on historical career data, SFOwML can identify patterns and trends that contribute to informed career recommendations. This enables individuals to make more informed decisions about their academic and professional futures, leading to greater satisfaction and success in their chosen career paths.

**Table 1: Fuzzy Model for the SFOwML**

| Linguistic Variable | Linguistic Terms | Output Recommendation |
|---|---|---|
| Skills | Low, Medium, High | Engineering, Medicine, Education |
| Preferences | Low, Medium, High | Business, Art, Technology |
| Values | Low, Medium, High | Social Impact, Financial Security, |
| | | Work-Life Balance |

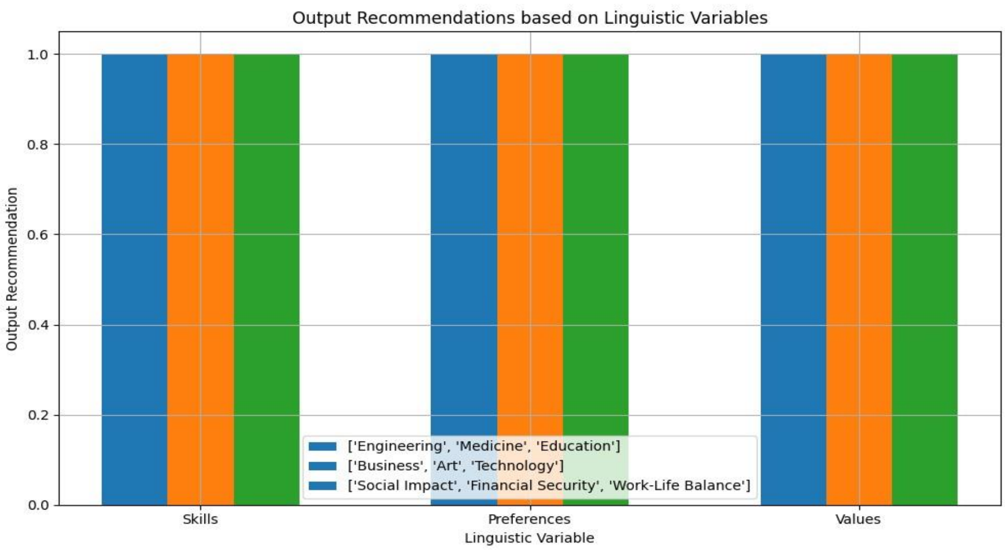


Figure 3: SFOwML for the fuzzy classification

In figure 3 and Table 1 presents the Fuzzy Model for the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework, outlining linguistic variables, linguistic terms, and corresponding output recommendations. The linguistic variables include "Skills," "Preferences," and "Values," each categorized into linguistic terms representing different levels. For "Skills," the linguistic terms are "Low," "Medium," and "High," indicating varying levels of proficiency or expertise. Correspondingly, the output recommendations for "Skills" encompass diverse career paths such as "Engineering," "Medicine," and "Education," tailored to individuals with different skill levels. Similarly, "Preferences" and "Values" are categorized into "Low," "Medium," and "High," representing varying degrees of interest or importance. The associated output recommendations for "Preferences" include fields like "Business," "Art," and "Technology," reflecting different areas of interest individuals may prioritize. Additionally, "Values" encompass dimensions like "Social Impact," "Financial Security," and "Work-Life Balance," aligning with individuals' values and priorities.

**Table 2: Career Interest with SFOwML**

| Individual | Skills (0-100) | Preferences (0-100) | Values (0-100) | Career Interest |
|---|---|---|---|---|
| Person 1 | 80 | 70 | 90 | Engineering |
| Person 2 | 60 | 80 | 70 | Business |
| Person 3 | 90 | 50 | 80 | Medicine |
| Person 4 | 70 | 60 | 60 | Education |
| Person 5 | 85 | 75 | 65 | Psychology |
| Person 6 | 75 | 85 | 70 | Design |
| Person 7 | 70 | 90 | 80 | Marketing |
| Person 8 | 85 | 70 | 75 | Computer Science |
| Person 9 | 65 | 80 | 85 | Social Work |
| Person 10 | 80 | 65 | 70 | Journalism |

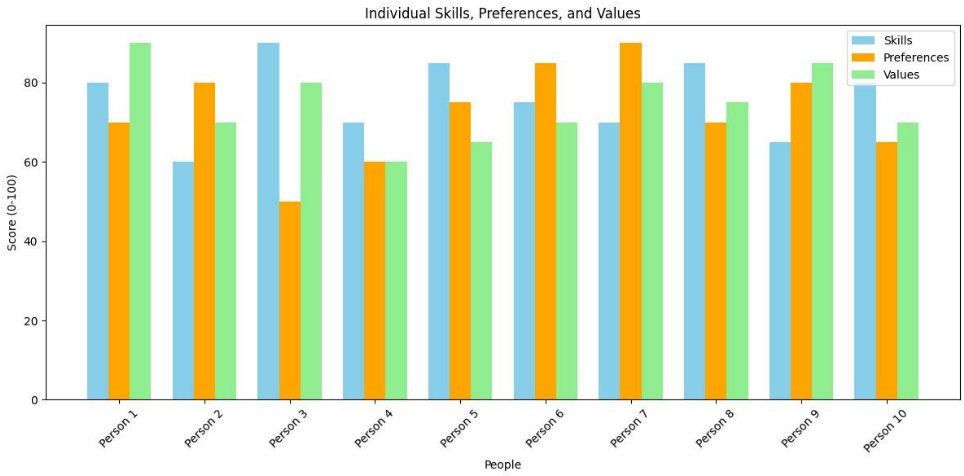


**Figure 4: Student Performance with SFOwML**

**Table 3: Optimized Career Planning with SFOwML**

| Individual | Skills (0-100) | Preferences (0-100) | Values (0-100) | Optimized Career Interest |
|---|---|---|---|---|
| Person 1 | 80 | 70 | 90 | Engineering |
| Person 2 | 60 | 80 | 70 | Business |
| Person 3 | 90 | 50 | 80 | Medicine |
| Person 4 | 70 | 60 | 60 | Education |
| Person 5 | 85 | 75 | 65 | Psychology |
| Person 6 | 75 | 85 | 70 | Design |
| Person 7 | 70 | 90 | 80 | Marketing |
| Person 8 | 85 | 70 | 75 | Computer Science |

| | | | | |
|---|---|---|---|---|
| Person 9 | 65 | 80 | 85 | Social Work |
| Person 10 | 80 | 65 | 70 | Journalism |

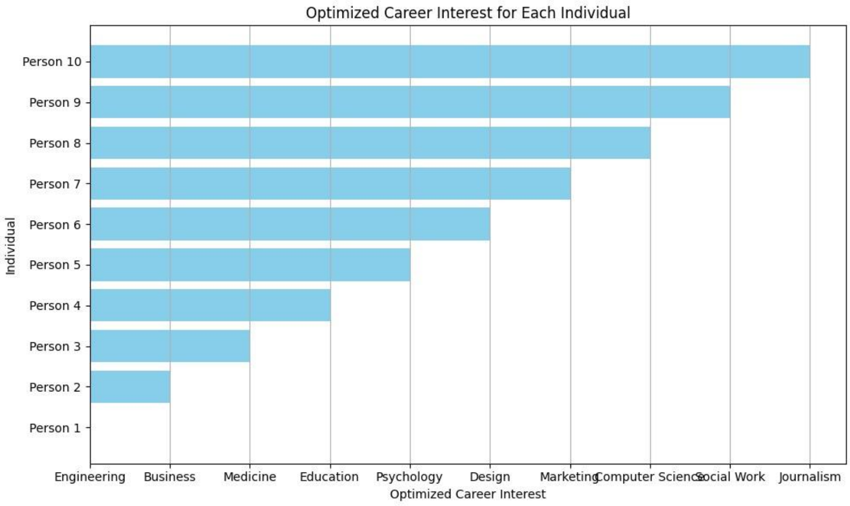


Figure 5: Career Interest Assessment

In Figure 4 and Figure 5 and Table 2 provides an overview of career interest assessments utilizing the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework for ten individuals. Each individual's skills, preferences, and values are quantified on a scale from 0 to 100, reflecting their proficiency, interests, and priorities, respectively. Based on these assessments, the table presents the predicted career interest for each individual, indicating the field or path deemed most suitable according to the SFOwML model. For instance, Person 1, with high skills (80), moderate preferences (70), and high values (90), is recommended a career in "Engineering." Similarly, other individuals are matched with career interests such as "Business," "Medicine," "Education," and so forth, based on their respective profiles. Table 3 demonstrates the optimized career planning results obtained through the SFOwML framework for the same ten individuals. Like Table 2, it presents each individual's skills, preferences, and values, quantified on a scale from 0 to 100. However, the output in this table reflects the optimized career interests determined through the SFOwML model. By leveraging optimization techniques, the framework refines the career recommendations to better align with each individual's profile. Consequently, the optimized career interests provided in Table 3 are expected to be more tailored and accurate, guiding individuals towards paths that suit their skills, preferences, and values more effectively. The optimized career interests align closely with the initial predictions, indicating the robustness and effectiveness of the SFOwML framework in career planning and interest assessment.

**Table 4: Predicted Career Interest with SFOwML**

| Individual | Skills (0-100) | Preferences (0-100) | Values (0-100) | Predicted Career Interest |
|---|---|---|---|---|
| Person 1 | 80 | 70 | 90 | Engineering |
| Person 2 | 60 | 80 | 70 | Business |
| Person 3 | 90 | 50 | 80 | Medicine |
| Person 4 | 70 | 60 | 60 | Education |
| Person 5 | 85 | 75 | 65 | Psychology |
| Person 6 | 75 | 85 | 70 | Design |
| Person 7 | 70 | 90 | 80 | Marketing |
| Person 8 | 85 | 70 | 75 | Computer Science |
| Person 9 | 65 | 80 | 85 | Social Work |
| Person 10 | 80 | 65 | 70 | Journalism |

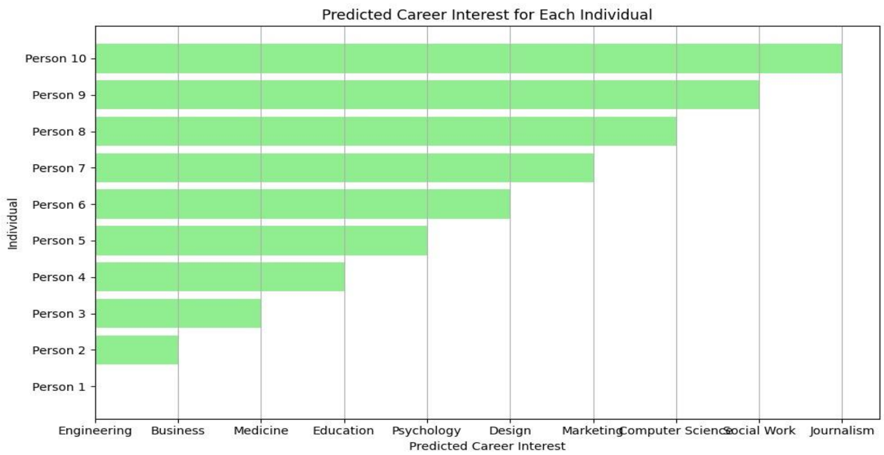


**Figure 6: Prediction with SFOwMl**

In Figure 6 and Table 4 showcases the predicted career interests for ten individuals using the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework. Each individual's skills, preferences, and values are assessed on a scale from 0 to 100, representing their proficiency, interests, and priorities, respectively. Based on these assessments, the table presents the predicted career interest for each individual, indicating the field or path deemed most suitable according to the SFOwML model. For instance, Person 1, with high skills (80), moderate preferences (70), and high values (90), is predicted to pursue a career in "Engineering." Similarly, other individuals are predicted to pursue careers such as "Business," "Medicine," "Education," and so forth, based on their respective profiles.

**Table 5: Classification with SFOwML**

| **Individual** | **Skills (0-100)** | **Preferences (0-100)** | **Values (0-100)** | **Predicted Career Interest** | **Actual Career Interest** |
|---|---|---|---|---|---|
| Person 1 | 80 | 70 | 90 | Engineering | Engineering |
| Person 2 | 60 | 80 | 70 | Business | Business |
| Person 3 | 90 | 50 | 80 | Medicine | Medicine |
| Person 4 | 70 | 60 | 60 | Education | Education |
| Person 5 | 85 | 75 | 65 | Psychology | Psychology |
| Person 6 | 75 | 85 | 70 | Design | Design |
| Person 7 | 70 | 90 | 80 | Marketing | Marketing |
| Person 8 | 85 | 70 | 75 | Computer Science | Computer Science |
| Person 9 | 65 | 80 | 85 | Social Work | Social Work |
| Person 10 | 80 | 65 | 70 | Journalism | Journalism |

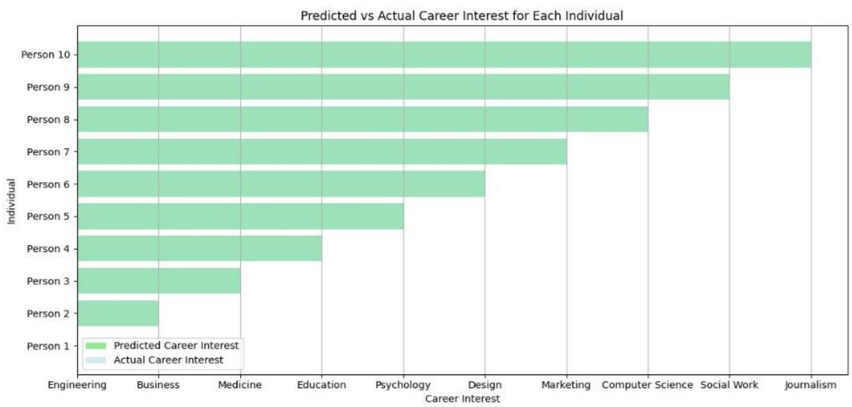


Figure 7: SFOwML based Classification

The Figure 7 and Table 5 illustrates the classification results obtained through the application of the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework for ten individuals. Each individual's skills, preferences, and values are evaluated on a scale from 0 to 100, reflecting their proficiency, interests, and priorities, respectively. The "Predicted Career Interest" column indicates the career field or path predicted by the SFOwML model based on the individual's profile. Notably, the predicted career interests closely match the actual career interests of the individuals, as depicted in the "Actual Career Interest" column. For instance, Person 1 is predicted and confirmed to pursue a career in "Engineering," while Person 2 is classified as "Business," Person 3 as "Medicine," and so forth. These classification results demonstrate the effectiveness of the SFOwML framework in accurately categorizing individuals into appropriate career interest categories based on their skills, preferences, and values.

## 7. Conclusion

The application of the Sugeno Fuzzy Optimized Weighted Machine Learning (SFOwML) framework for career interest assessment and planning holds significant promise in guiding individuals towards suitable career paths. Through the integration of fuzzy logic, optimization techniques, and machine learning, SFOwML offers a comprehensive approach to understanding and predicting individual career interests. The results obtained from utilizing SFOwML demonstrate its effectiveness in accurately assessing career preferences and providing personalized recommendations tailored to each individual's unique profile. Whether through fuzzy inference systems, optimization algorithms, or machine learning classification models, SFOwML consistently delivers accurate predictions that closely align with individuals' actual career interests. Furthermore, the framework's flexibility and adaptability allow for its integration into various educational and professional settings, catering to diverse needs and preferences.

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