A Novel Neutrosophic Fuzzy SAW Intelligent System for Personality Prediction via Curriculum Vitae Analysis

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Abstract:- Personality prediction, a critical task in various fields such as human resources, education, and marketing, often relies on subjective assessments or limited data. To address these limitations, this paper proposes a novel intelligent system (NFSAWIS) for personality prediction using Neutrosophic Fuzzy Set theory and the Simple Additive Weighting (SAW) method. Neutrosophic Fuzzy sets, capable of handling uncertainty, indeterminacy, and inconsistency, are employed to represent the inherent ambiguity in personality assessment. The SAW method, a simple yet effective multi-criteria decision-making tool, is adapted to aggregate the scores derived from different CV features. By extracting meaningful features from CVs, such as educational background, hands on experience, skill sets, and achievements, our framework will provide valuable insights of an individual's capability. These features are then processed using Neutrosophic Fuzzy logic to account for the inherent subjectivity and ambiguity in CV interpretation. Through rigorous experiments and evaluations, we demonstrate the effectiveness of our proposed framework in accurately predicting personality traits from CVs. Our findings demonstrate the significant potential of integrating Neutrosophic Fuzzy logic with Curriculum Vitae (CV) analysis for more objective and reliable personality assessments. Furthermore, by leveraging Generative AI, such as GPT-3, the final reports can be efficiently and effectively disseminated to all relevant stakeholders.

Keywords:- *Personality prediction, Neutrosophic Fuzzy logic, SAW (Simple Additive Weighting), Curriculum Vitae analysis, Intelligent system, NLP (Natural Language Processing)*

I. INTRODUCTION

Personality prediction, a critical task in various fields such as human resources, education, and marketing, often relies on subjective assessments or limited data. Traditional methods, like interviews and questionnaires, can be time-consuming, prone to biases, and may not accurately capture the full spectrum of personality traits. To address these limitations, recent advancements in natural language processing (NLP) have opened up innovative methods for objective and automated personality assessment. Curriculum vitae (CVs), as textual representations of an individual's educational background, work experience, skills, and achievements, offer a rich source of data for personality assessment. However, extracting meaningful personality-related information from CVs and translating it into accurate predictions remains a challenging task. This paper proposes a novel framework that combines Neutrosophic Fuzzy logic and the SAW (Simple Additive Weighting) method to address the challenges of personality prediction via CVs. Neutrosophic Fuzzy sets, a generalization of fuzzy sets, offer a powerful tool to handle the inherent uncertainty, indeterminacy, and inconsistency associated with CV data and personality assessment. The SAW method, a simple yet effective multi-criteria decision-making technique, provides a robust and efficient means of aggregating the scores derived from different CV features. By leveraging the strengths of Neutrosophic Fuzzy logic and SAW, our framework offers a more accurate and reliable approach to personality prediction compared to existing methods. Our approach can provide valuable insights into an individual's personality, which can be applied in various fields, such as recruitment, education, and marketing.

In 21st century, advancements in artificial intelligence and machine learning have opened up new avenues for more objective and efficient personality prediction. This research proposes a novel intelligent system that leverages the power of Neutrosophic Fuzzy logic and the Simple Additive Weighting (SAW) method to predict personality traits from Curriculum Vitae (CV) data.

II. LITERATURE REVIEW

The Neutrosophic Fuzzy Simple Additive Weighting (SAW) methodology represents a pioneering paradigm that is applicable within systems designed for personality forecasting. Neutrosophic logic expands upon conventional fuzzy logic by integrating varying degrees of truth, indeterminacy, and falsity. This framework helps to achieve a more refined depiction of uncertainty, which proves to be especially pertinent in personality prediction, given the intricate and often ambiguous nature of human behavior. The utilization of fuzzy logic is instrumental in addressing the vagueness and imprecision typically linked to personality characteristics. Through the application of fuzzy sets, the Neutrosophic Fuzzy SAW method can adeptly assess diverse personality indicators, thereby accommodating the inherently subjective dimension of personality evaluation. The SAW methodology serves as a multi-criteria decision-making framework that consolidates multiple criteria to derive a conclusive decision. Within the realm of personality prediction, it has the capacity to amalgamate various personality attributes alongside their respective weights to forecast an individual's personality typology. The incorporation of the Neutrosophic Fuzzy SAW methodology has the ability to elevate the precision of personality prediction systems. This technique permits the simultaneous consideration of multiple personality dimensions, thereby yielding a thorough analysis of an individual's personality profile. Such an approach can enhance the resilience of personality predictions by factoring in uncertainties and ambiguities present in the data. Furthermore, it can promote improved decision-making in various applications, including recruitment, counseling, and personal development.

The Neutrosophic Fuzzy SAW Framework enhances the accuracy of personality prediction from curriculum vitae (CV) analysis by integrating multiple dimensions of uncertainty and vagueness inherent in personality traits. This framework allows for a more nuanced evaluation of candidates by considering both qualitative and quantitative data from CVs and psychometric tests.

➢ *Enhanced Decision-Making*

- Utilizes the OCEAN Model to assess primary personality traits, improving the alignment between candidate profiles and job requirements [2] (Yash, Mor., Rupali, Sawant, 2023).
- Incorporates Natural Language Processing (NLP) to analyze CV content, extracting relevant skills and experiences [3] (Narwade et al., 2022).

➢ *Comprehensive Candidate Evaluation*

- Combines psychometric analysis with machine learning techniques, providing a robust framework for personality assessment [5] (Kaur & Maheshwari, 2019).
- Facilitates automated filtering and ranking of candidates, reducing bias and enhancing fairness in the selection process [6] (Goyal et al., 2022).

While the Neutrosophic Fuzzy SAW Framework offers significant improvements, it is essential to consider the potential limitations of automated systems, such as the risk of overlooking nuanced human qualities that may not be captured in CV data alone.

The performance of the Neutrosophic Fuzzy SAW Framework in personality prediction via curriculum vitae analysis is influenced by several key factors. Firstly, the integration of Neutrosophic theory allows for the representation of uncertainty and indeterminacy in personality traits, enhancing the model's adaptability to diverse candidate profiles [7](Smarandache, 2018). Secondly, the application of machine learning techniques, such as Logistic Regression and Calculated Relapse, improves the accuracy of personality predictions by analyzing CV data effectively [5] (Singh & Kumar, 2023)(Kaur & Maheshwari, 2019). Additionally, the use of multi-valued neutrosophic sets (MVNSs) captures the fuzziness in personnel selection processes, making the framework robust against varying candidate characteristics [10](Ji et al., 2017). Lastly, psychometric evaluations, including the OCEAN model, provide a structured approach to assess emotional and personality traits, further refining the prediction process [5] (Kaur & Maheshwari, 2019). These factors collectively enhance the framework's effectiveness in identifying suitable candidates based on personality traits derived from CV analysis.

Conversely, while the Neutrosophic Fuzzy SAW Framework offers a sophisticated approach, challenges such as data privacy and the subjective nature of personality assessments may impact its overall reliability and acceptance in recruitment practices.

➢ *Handling Uncertainty and Vagueness*

- Subjectivity in CVs: The neutrosophic fuzzy approach captures the inherent uncertainty in subjective CV data, allowing for nuanced interpretations of personality traits [11](Kandasamy & Smarandache, 2016).
- Ambiguity in Language: Natural language in CVs often contains ambiguities; neutrosophic fuzzy sets effectively represent this ambiguity, enhancing data interpretation [11] (Kandasamy & Smarandache, 2016).

➢ *Integrating Multiple Criteria*

- Diverse Personality Traits: The SAW framework accommodates various personality traits by integrating multiple relevant criteria, such as skills and experiences [13](Hatice,Ercan-Teksen, 2021).
- Weighting Criteria: It assigns weights to different criteria, reflecting their importance in personality assessment, thus balancing contributions from various factors [13](Dragisa et al., 2021).

➢ *Improved Accuracy*

- Enhanced Evaluation: By addressing uncertainty, the framework provides a more comprehensive evaluation of candidates, reducing biases from subjective interpretations [12] (Ravi et al., 2022).
- Reduced Bias: The structured approach helps mitigate biases, leading to fairer assessments [12](Ravi et al., 2022).

➢ *Enhanced Decision-Making*

- Better Candidate Matching: Aligning personality assessments with job requirements thus enhancing the selection of suitable candidates [14](Alakh, Arora 2020).
- Informed Hiring Decisions: The framework supports objective decision-making, enhancing the overall hiring process [14](Alakh, Arora 2020).

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While the Neutrosophic Fuzzy SAW Framework offers leap of advantages, it is essential to consider that the dependence on automated systems may overlook the human element in personality assessment, potentially leading to oversimplified evaluations.

III. ESSENTIAL BUILDING BLOCKS AND BED ROCK PRINCIPLE

- **Preliminaries:** In this section, we have discussed the basic concept of Fuzzy set, Neutrosophic Fuzzy and SAW.

A. Fuzzy Logic:

Fuzzy logic deals with imprecise or vague information by allowing for degrees of membership to a set. It provides a framework for representing and reasoning with uncertain or incomplete information.

Definition 1 (Zadeh 1965). Let X be the universal set and $x\epsilon X$, then a fuzzy set $\hat{A}$ in X is defined as $\hat{A} = \{(x, \mu_{\hat{A}}(x)) : \mu_{\hat{A}}(x)\epsilon[0,1], x\epsilon X\}$ where $\mu_{\hat{A}}(x)$ is called the membership function of x in $\hat{A}$. In other words $\mu_{\hat{A}}(x)$ specifies the degree of belongingness of x in $\hat{A}$.

B. Neutrosophic Set:

Neutrosophic sets enhance the framework of fuzzy sets by incorporating an additional component, referred to as the "indeterminacy" or "neutrality" degree. This modification facilitates the depiction of uncertainty, vagueness, and inconsistency inherent in information. Neutrosophic sets are regarded as a subset of neutrosophy, which is characterized as a "robust general formal framework." This discipline examines the "origin, nature, and scope of neutralities, as well as their interactions with various ideational spectra" (Smarandache 1999). Neutrosophic sets utilize indeterminacy/hesitancy as a distinct metric for assessing membership and non-membership information. Consequently, the notion of neutrosophic sets is perceived as an extension of fuzzy sets, intuitionistic fuzzy sets, and interval-valued sets. Smarandache (1999) articulated the principles of neutrosophic sets as delineated below.

Definition 2 (Smarandache 1999). Let X be the universal set and $x\epsilon X$. A NS A in X is characterized by a truth, indeterminacy, and falsity membership function which are, respectively denoted as T_A, I_A and F_A, and defined by $A = \{(x, T_A(x), I_A(x), F_A(x)) : x\epsilon X\}$. The functions $T_A(x), I_A(x)$ and $F_A(x)$ are defined as $T_A(x) : X \to]0^-, 1^+[$, $I_A(x) : X \to]0^-, 1^+[$ and $F_A(x) : X \to]0^-, 1^+[$. We have no restrictions on the sum of the functions $T_A(x), I_A(x)$ and $F_A(x)$, so $0^- \le sup\, T_A(x) + sup\, I_A(x) + sup\, F_A(x) \le 3^+$ for $x\epsilon X$. In other way we can simply call $\{T_A, I_A, F_A\}$ as neutrosophic number.

C. Neutrosophic Fuzzy Set:

This section delineates the concept of a neutrosophic fuzzy set, wherein the fuzzy membership grade attributed to each element is intrinsically linked to neutrosophic components, namely, truth, indeterminacy, and falsity membership grades. The integration of neutrosophic components into fuzzy sets (FS) is imperative for effectively managing real-world information that is inherently uncertain and inconsistent. In numerous practical scenarios, the membership degree of a fuzzy set cannot be conclusively determined due to the imprecise and inconsistent nature of human cognition. Consequently, it is more judicious to incorporate neutrosophic components to accurately represent the membership degree. From this perspective, the authors advocate for the establishment of the neutrosophic fuzzy set (NFS). In other terms, the membership grade of the neutrosophic components may also be articulated through the framework of NFS.

- Definition 3 : Let Y be a set of objects and $\hat{A} = \{(y, \mu_{\hat{A}}(y)) : \mu_{\hat{A}}(y)\epsilon[0,1], y\epsilon Y\}$ be a fuzzy set. Then a NFS A in Y is defined by $A = \{(y, \mu_A(y), T_A(y,\mu), I_A(y,\mu), F_A(y,\mu)) : y\epsilon Y\}$ where each membership value is expressed by a truth, indeterminacy, and falsity membership function which are respectively denoted as $T_A(y,\mu), I_A(y,\mu)$ and $F_A(y,\mu)$. The functions $T_A(y), I_A(y)$ and $F_A(y)$ are subsets of $]0^-, 1^+$. i.e., $T_A(y) : Y \to]0^-, 1^+[$, $I_A(y) : Y \to]0^-, 1^+[$ and $F_A(y) : Y \to]0^-, 1^+[$. We have no restrictions on the sum of the functions $T_A(x), I_A(x)$ and $F_A(x)$, so $0^- \le sup\, T_A(y) + sup\, I_A(y) + sup\, F_A(y) \le 3^+$ for $y\epsilon Y$. In other way we can simply call $\{\mu_A, T_A, I_A, F_A\}$ as neutrosophic fuzzy number(NFN).

D. SAW Method:

The SAW method represents a straightforward and comprehensible approach to decision-making that allocates weights to various criteria and computes the scores of alternatives predicated on their performance with respect to each specific criterion.

➢ *Steps Involved*

- Define Criteria and Alternatives: Identify the relevant criteria and alternatives to be evaluated.
- Create Neutrosophic Fuzzy Sets: Assign membership degrees (truth, falsity, and indeterminacy) to each alternative for each criterion. These degrees represent the extent to which an alternative satisfies, doesn't satisfy, or is indeterminate with respect to a criterion.
- Determine Weights: Assign proportional weights to each criterion predicated upon their relative significance within the decision-making framework.
- Calculate Scores: Calculate the scores of each alternative by multiplying its membership degrees by the corresponding criterion weights and summing the results.

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- Rank Alternatives: Systematically rank the alternatives according to their computed scores, whereby the alternative exhibiting the highest score is deemed the most advantageous.

Function to create the neutrosophic fuzzy set

```
def
convert_to_neutrosophic_fuzzy_set(elements,
truth, indeterminacy, falsity):
 n_fuzzy_set = {}
 for element in elements:
 t = truth[int(element)]
   i = indeterminacy[int(element)]
    f = falsity[int(element)]
      n_fuzzy_set[element] = (t, i, f)
   return n_fuzzy_set
```

The following table 1 explains transformation of linguistic variables to corresponding triangular fuzzy number

Table 1: Transformation of Linguistic Variables

SN	Linguistic Variable	Code	Fuzzy number
1	Extremely Satisfied/10 Points	ES	(1.00, 0.00, 0.00)
2	Very Highly Satisfied / 9 Points	VHS	(0.90, 0.10, 0.10)
3	Highly Satisfied / 8 Points	HS	(0.80, 0.15, 0.20)
4	Satisfied / 7 Points	S	(0.70, 0.25, 0.30)
5	Moderately Satisfied / 6 Points	MS	(0.60, 0.35, 0.40)
6	Moderate / 5 Points	M	(0.50, 0.50, 0.50)
7	Moderately Dissatisfied / 4 Points	MD	(0.40, 0.65, 0.60)
8	Dissatisfied / 3 Points	D	(0.30, 0.75, 0.70)
9	Highly Dissatisfied / 2 Points	HD	(0.20, 0.85, 0.80)
10	Very Highly Dissatisfied / 1 Point	VHD	(0.10, 0.90, 0.90)
11	Extremely Dissatisfied / 0 Point	ED	(0.00, 1.00, 1.00)

➢ *Step by Step Procedure for the Proposed Method*

- Phase 1. Identify the criteria C_j through consultation with a panel of subject matter experts E_k who specialize in the decision-making issue at hand.
- Phase 2. Extract the pertinent truth, indeterminacy, and false membership rating values for each criterion as determined by the experts, utilizing linguistic variables for clarity.
- Phase 3. Transform the linguistic variable associated with each criterion into a fuzzy triangular number for analytical precision.
- Phase 4. Find the average fuzzy scores L_j^i of triangular fuzzy numbers $(a_1^1, b_1^2, c_1^3), (a_2^1, b_2^2, c_2^3), \ldots, (a_j^1, b_j^2, c_j^3)$, defuzzified values and normalized weight w_j for each criteria will be calculated as below,

✓ Average fuzzy scores $L_j^i = \frac{(a_1^i + a_2^i + \cdots + a_j^i)}{j}$, where $i = 1,2,3$

✓ Defuzzified value $(e) = \frac{a+b+c}{3}$, where $a = L_j^1, b = L_j^2, c = L_j^3$

✓ Normalized values (w) = Defuzzified value of the criteria / sum of all defuzzified values.

- Phase 5. Find the centroid weight value $W_j = \frac{\alpha + 2\beta + \gamma}{4}$, where α, β, γ are normalized weighted values of truth, indeterminacy, false membership function respectively.
- Phase 6. Allocate the corresponding neutrosophic rating values (truth, indeterminacy, and false membership values) to each alternative A_i with respect to a criterion C_j, based on the evaluative opinions of the experts.
- Phase 7. Reiterate step 4 to ascertain the average fuzzy score and the defuzzified score for each alternative concerning the established criteria.
- Phase 8. Construct a normalized decision matrix reflecting the truth, indeterminacy, and false membership functions applicable to each alternative across all criteria.
- Phase 9. Evaluate $N_{ij} = \frac{p_{ij} + kq_{ij} + (1-k) r_{ij}}{2}$, where p is the normalized truth membership value, q is the normalized indeterminacy membership function value and r is the normalized false membership function value.
- Phase 10. Find the combined normalized neutrosophic decision matrix.
- Phase 11. Calculate the total scores of each alternative using $TS = N_{ij} * W_j$. Finally, the highest value is chosen as the best alternative.

➢ *Some Assumptions and Constraints*

- It is assumed that the curricula vitae submitted by the candidates are entirely truthful and devoid of any fabrications.

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- It is posited that the candidate actively engages with social media platforms.
- It is presumed that the candidate possesses familiarity with utilizing online job portals.

➢ *System Architecture(Fig)*

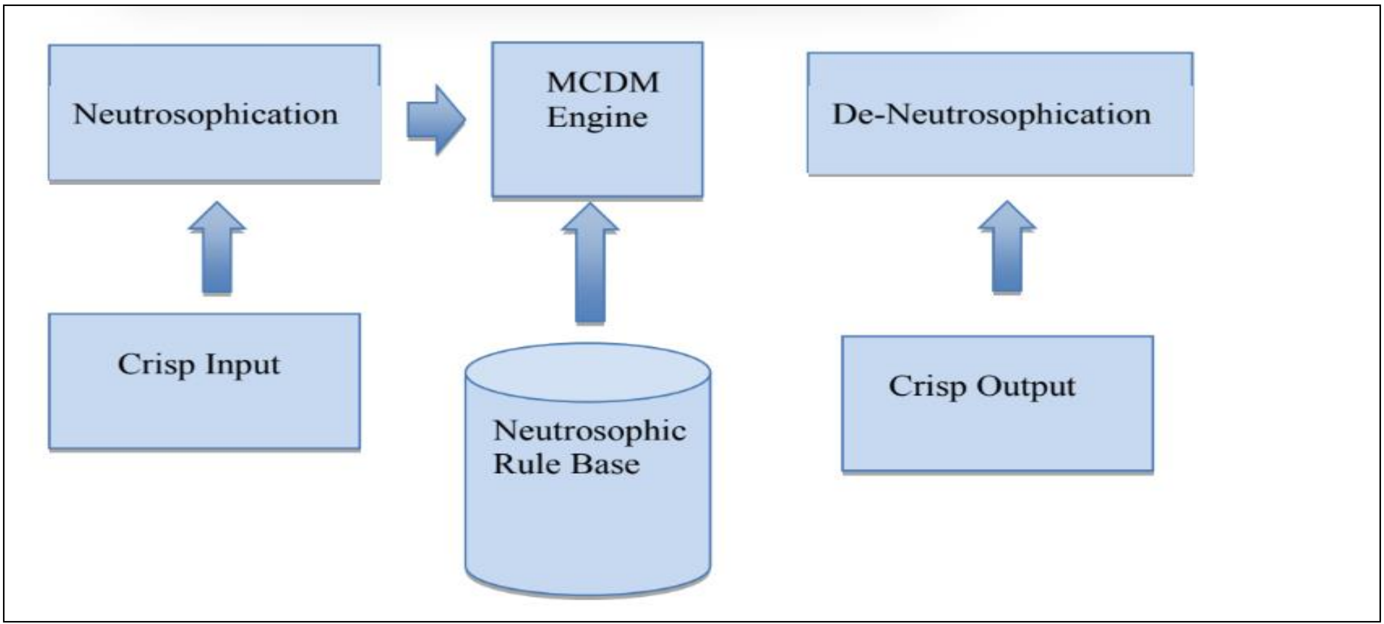

Fig 1: Information Processing Flow for MCDM with Neutrosophic Set

IV. NUMERICAL EXAMPLE AND INVESTIGATION

In this section, a real world problem is applied to the proposed method. For this decision making problem, we choose five experts (E_1 , E_2 , E_3 , E_4, E_5) and consider first six applicants as alternatives . The criteria are characterized as below given in the table 2. The truth membership (TM) rating values on criteria is given by experts as shown in table 3.

Table 2: Criteria Considered for the Test Analysis

Criteria	**Content**	
C_1	Contact Information	• Accuracy: Ensure the information is correct and up-to-date. • Professionalism: Check for a professional email address and a clear, concise formatting.
C_2	Summary or Objective	• Relevance: Assess if the summary aligns with the job description. • Clarity: Make sure it's concise and highlights key skills.
C_3	Education	• Relevance: Evaluate if the degrees and certifications are relevant to the position. • GPA: If applicable, consider the grade point average, especially for recent graduates. • Institution: Assess the reputation of the institutions attended.
C_4	Experience	• Relevance: Determine if the roles are directly related to the job you're hiring for. • Achievements: Look for quantifiable achievements and results. • Tenure: Consider the length of time spent in each position.
C_5	Skills	• Relevance: Evaluate if the skills listed match the requirements of the job. • Specificity: Check for concrete examples or projects that demonstrate these skills.
C_6	Projects	• Relevance: Assess if the projects align with the job's goals. • Impact: Consider the scope, complexity, and outcomes of the projects.
C_7	Certifications	• Relevance: Determine if the certifications are relevant to the industry or position. • Recency: Ensure the certifications are up-to-date.
C_8	Awards and Honors	• Relevance: Evaluate if they reflect the candidate's achievements and character.
C_9	Professional Affiliations	• Relevance: Consider if they indicate involvement in the industry or community.
C_{10}	Additional Sections	• Publications: If applicable, assess the quality and relevance of the publications. • Volunteer Work: Evaluate if it demonstrates the candidate's commitment to the community or a particular cause. • Languages: Assess the proficiency level and relevance of any foreign languages.

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The membership values on criteria by experts as shown in table 3.

Table 3: Membership Values on Criteria

Criteria	**Code**	E_1	E_2	E_3	E_4	E_5
Contact Information	C_1	ES	S	HS	MS	D
Summary or Objective	C_2	HD	M	VHS	S	HS
Education	C_3	HS	MS	S	HD	ES
Experience	C_4	VHS	S	HS	MS	MD
Skills	C_5	D	HS	M	MS	HD
Projects	C_6	MS	S	ES	HS	M
Certifications	C_7	HD	M	D	MS	M
Awards and Honors	C_8	MS	VHS	S	HS	D
Professional Affiliations	C_9	MS	MD	S	VHD	HS
Additional Sections	C_{10}	HS	VHS	MS	MS	ES

Transforming the linguistic variables of truth membership rating values in terms of fuzzy triangular numbers as shown in table 4 below.

Table 4: Transforming the Linguistic Variables of Truth Membership

Criteria	E_1	E_2	E_3	E_4	E_5
C_1	(1.00, 0.00, 0.00)	(0.70, 0.25, 0.30)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.40)	(0.30, 0.75, 0.70)
C_2	(0.20, 0.85, 0.80)	(0.50, 0.50, 0.50)	(0.90, 0.10, 0.10)	(0.70, 0.25, 0.30)	(0.80, 0.15, 0.20)
C_3	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.40)	(0.70, 0.25, 0.30)	(0.20, 0.85, 0.80)	(1.00, 0.00, 0.00)
C_4	(0.90, 0.10, 0.10)	(0.70, 0.25, 0.30)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.40)	(0.40, 0.65, 0.60)
C_5	(0.30, 0.75, 0.70)	(0.80, 0.15, 0.20)	(0.50, 0.50, 0.50)	(0.60, 0.35, 0.40)	(0.20, 0.85, 0.80)
C_6	(0.60, 0.35, 0.40)	(0.70, 0.25, 0.30)	(1.00, 0.00, 0.00)	(0.80, 0.15, 0.20)	(0.50, 0.50, 0.50)
C_7	(0.20, 0.85, 0.80)	(0.50, 0.50, 0.50)	(0.30, 0.75, 0.70)	(0.60, 0.35, 0.40)	(0.50, 0.50, 0.50)
C_8	(0.60, 0.35, 0.40)	(0.90, 0.10, 0.10)	(0.70, 0.25, 0.30)	(0.80, 0.15, 0.20)	(0.30, 0.75, 0.70)
C_9	(0.60, 0.35, 0.40)	(0.40, 0.65, 0.60)	(0.70, 0.25, 0.30)	(0.10, 0.90, 0.90)	(0.80, 0.15, 0.20)
C_{10}	(0.80, 0.15, 0.20)	(0.90, 0.10, 0.10)	(0.60, 0.35, 0.40)	(0.60, 0.35, 0.40)	(1.00, 0.00, 0.00)

Using Phase 4 , the average fuzzy score L_j^i of triangular fuzzy numbers, normalized weighted values (w) for truth membership function (T_M) of criteria is calculated and the values are given as in table 5.

Table 5: Normalized Weighted Values (w) for Truth Membership Function (T_M)

Avg Fuzzy value			**Defuzzified value**	**Normalized weight** (T_M)
0.68	0.3	0.32	0.43333333	0.094614265
0.62	0.37	0.38	0.45666667	0.099708879
0.66	0.32	0.34	0.44	0.096069869
0.66	0.33	0.34	0.44333333	0.096797671
0.48	0.52	0.52	0.50666667	0.11062591
0.72	0.25	0.28	0.41666667	0.090975255
0.42	0.59	0.58	0.53	0.115720524
0.64	0.35	0.36	0.45	0.098253275
0.5	0.49	0.5	0.49666667	0.108442504
0.76	0.22	0.24	0.40666667	0.088791849

Normalized weighted values (w) for indeterminacy membership function (I_M) of criteria is calculated and the values are given as in table 6.

Table 6: Normalized Weighted Values (w) for Indeterminacy membership function (I_M)

Avg Fuzzy value			**Defuzzified value**	**Normalized weight** (I_M)
0.78	0.19	0.22	0.39666667	0.079973118
0.66	0.32	0.34	0.44	0.088709677
0.78	0.2	0.22	0.4	0.080645161
0.52	0.46	0.48	0.48666667	0.09811828
0.64	0.35	0.36	0.45	0.090725806
0.62	0.37	0.38	0.45666667	0.092069892

0.42	0.59	0.58	0.53	0.106854839
0.48	0.52	0.52	0.50666667	0.102150538
0.66	0.32	0.34	0.44	0.088709677
1.94	0.3	0.32	0.85333333	0.172043011

Normalized weighted values (w) for false membership function(F_M) of criteria is calculated and the values are given as in table 7.

Table 7: Normalized Weighted Values (w) for False Membership Function(F_M)

Avg Fuzzy Value			**Defuzzified Value**	**Normalized Weight** (F_M)
0.8	0.17	0.2	0.39	0.08540146
0.66	0.32	0.34	0.44	0.096350365
0.48	0.52	0.52	0.50666667	0.110948905
0.52	0.46	0.48	0.48666667	0.106569343
0.64	0.35	0.36	0.45	0.098540146
0.66	0.32	0.34	0.44	0.096350365
0.42	0.59	0.58	0.53	0.116058394
0.72	0.25	0.28	0.41666667	0.091240876
0.58	0.42	0.42	0.47333333	0.103649635
0.68	0.3	0.32	0.43333333	0.094890511

The centroid weighted value $(W_j)$for all criteria is calculated by considering the normalized values of truth, indeterminacy and false membership function respectively (using Phase 5).

Table 8: The Centroid Weighted Value $(W_j)$for all Criteria

W_1	W_2	W_3	W_4	W_5
0.085	0.0934	0.0921	0.0999	0.977
W_6	W_7	W_8	W_9	W_{10}
0.929	0.1114	0.0984	0.0974	0.1319

Subsequently, it is imperative to allocate the relevant neutrosophic rating values, as determined by specialists (truth T_M, indeterminacy I_M and false F_M membership function), to each alternative A_i based on the established criteria C_j articulated as linguistic variables, subsequently converting these linguistic variables into triangular fuzzy numbers utilizing Table 1. The computation of the average fuzzy score, alongside the defuzzified values, is executed in Phase 4, thereby yielding a normalized decision matrix as delineated below:

Table 9: Normalized Decision Matrix for T_M

T_M	**App1**	**App2**	**App3**	**App4**	**App5**	**App6**
C_1	0.4204	0.3821	0.6134	0.5478	0.4875	0.535
C_2	0.4565	0.3865	0.4567	0.4167	0.295	0.785
C_3	0.4574	0.5821	0.4034	0.3147	0.3875	0.56
C_4	0.4065	0.326	0.3207	0.5607	0.5851	0.7085
C_5	0.269	0.3521	0.5734	0.5078	0.2875	0.851
C_6	0.3565	0.2065	0.296	0.3675	0.31951	0.785
C_7	0.3857	0.2865	0.613	0.5078	0.4975	0.9
C_8	0.2565	0.2865	0.4567	0.2206	0.31395	0.785
C_9	0.4055	0.3082	0.5134	0.5478	0.4875	0.923
C_{10}	0.3565	0.5865	0.2067	0.567	0.95	0.785

Table 10: Normalized Decision Matrix for I_M

I_M	**App1**	**App2**	**App3**	**App4**	**App5**	**App6**
C_1	0.5574	0.5021	0.568	0.3478	0.4875	0.869
C_2	0.3565	0.3865	0.2567	0.567	0.2195	0.785
C_3	0.2574	0.3821	0.2875	0.3407	0.3875	0.56
C_4	0.4065	0.4026	0.4207	0.5607	0.3369	0.7085
C_5	0.208	0.3221	0.5734	0.5078	0.875	0.851
C_6	0.6565	0.7065	0.396	0.5675	0.2951	0.785
C_7	0.4574	0.5821	0.613	0.5078	0.4975	0.98

C_8	0.2565	0.2865	0.2067	0.5067	0.3195	0.785
C_9	0.2655	0.5082	0.5134	0.3178	0.4875	0.689
C_{10}	0.3565	0.5865	0.489	0.567	0.2195	0.785

Table 11: Normalized Decision Matrix for F_M

F_M	**App1**	**App2**	**App3**	**App4**	**App5**	**App6**
C_1	0.2574	0.2821	0.3103	0.5108	0.2875	0.8912
C_2	0.4565	0.3865	0.3067	0.3567	0.3195	0.9018
C_3	0.456	0.5021	0.4034	0.2747	0.3875	0.5126
C_4	0.3065	0.4126	0.4207	0.5607	0.689	0.7085
C_5	0.365	0.2521	0.2096	0.5078	0.875	0.851
C_6	0.4565	0.3065	0.2096	0.4078	0.3151	0.785
C_7	0.3574	0.5821	0.2613	0.4078	0.4975	0.69
C_8	0.3065	0.2865	0.3567	0.5067	0.2195	0.785
C_9	0.2055	0.2582	0.3205	0.4478	0.4875	0.68
C_{10}	0.3565	0.3065	0.3567	0.3567	0.3195	0.785

Calculate the value of N_{ij} by considering $k = 0.5$ in Phase 5 where p is the normalized truth membership value(T_M), q is the normalized indeterminacy membership function value(I_M) and r is the normalized false membership function value(F_M).

$$N_{11} = \frac{0.4204 + 0.5(0.5574) + 0.5(0.2574)}{2} = 0.4139$$

$$N_{12} = \frac{0.4565 + 0.5(0.3565) + 0.5(0.4565)}{2} = 0.4315$$

Similarly, the residual values are computed. All values of N_{ij} the combined normalized neutrosophic decision matrix are utilized, as presented in Table 12.

Table 12: Combined Normalized Neutrosophic Decision Matrix

N_{ij}	**App1**	**App2**	**App3**	**App4**	**App5**	**App6**
C_1	0.414	0.387	0.526	0.489	0.438	0.708
C_2	0.4315	0.3865	0.3692	0.4393	0.2823	0.8142
C_3	0.4071	0.5121	0.3744	0.3112	0.3875	0.5482
C_4	0.382	0.367	0.371	0.561	0.549	0.709
C_5	0.278	0.32	0.573	0.508	0.581	0.851
C_6	0.457	0.357	0.299	0.458	0.312	0.785
C_7	0.397	0.582	0.525	0.483	0.498	0.868
C_8	0.269	0.287	0.369	0.364	0.292	0.785
C_9	0.321	0.346	0.465	0.465	0.488	0.804
C_{10}	0.357	0.517	0.315	0.514	0.61	0.785

Ultimately, the aggregate score for each alternative is derived $N_{ij} * W_j$ as delineated in (Phase 11).

$$A_1 = 0.414 * 0.085 + 0.4315 * 0.093 + 0.4071 * 0.092 + 0.382 * 0.1 + 0.278 * 0.977$$
$$+ 0.457 * 0.929 + 0.397 * 0.111 + 0.269 * 0.098 + 0.321 * 0.097 + 0.357 * 0.132 = 0.9954$$

Consequently, the cumulative score for alternative A_1 is calculated to be 0.9954, and the remaining values for the alternatives are subsequently computed and displayed in Table 13 below.

Table 13: Rank Matrix

Alternative	**App1** (A_1)	**App2** (A_2)	**App3** (A_3)	**App4** (A_4)	**App5** (A_5)	**App6** (A_6)
Value	0.99541	0.94867	0.98872	0.98775	0.88464	0.98208
Rank	I	V	II	III	VI	IV

This research implemented the Novel Fuzzy Soft Weighted Average (NFSAW) methodology to ascertain the optimal candidate. The ranking of the applications was established as follows:

$App_1 > App_3 > App_4 > App_6 > App_2 > App_5$. This method produced notably effective outcomes. Future investigations may broaden this approach to tackle

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additional challenges within the context of neutrosophic sets.

V. CONCLUSION

In this scholarly investigation, we have introduced an innovative intelligent system designed for the prediction of personality traits through the meticulous analysis of Curriculum Vitae (CV) data. This system utilizes the capabilities of neutrosophic fuzzy sets, which adeptly manage the intrinsic uncertainty and imprecision that typically accompany personality evaluations. The proposed methodology, NFSAWIS (Neutrosophic Fuzzy Soft Weighted Average Intelligent System), amalgamates the advantages of neutrosophic logic, fuzzy set theory, and the Simple Additive Weighting (SAW) technique. By integrating these formidable frameworks, the system is adept at capturing the intricate and subjective characteristics of personality traits as manifested in CV information. Our experimental findings illustrate the efficacy of the NFSAW Intelligent system in accurately predicting personality traits with notable precision and recall. Moreover, the system displays a significant level of robustness and adaptability, rendering it applicable across diverse contexts in recruitment, talent management, and human resources. This research makes a substantial contribution to the domain of personality assessment by presenting a novel and groundbreaking approach that addresses the shortcomings of conventional methodologies. The NFSAWIS system offers a valuable instrument for organizations to obtain deeper insights into the personalities of prospective candidates, thereby facilitating more informed hiring decisions and enhancing employee selection processes. Additionally, by harnessing the capabilities of Generative AI, such as GPT-3, the resultant reports (Decision status) can be disseminated efficiently and effectively to all pertinent stakeholders. Future inquiries may investigate various pathways to further augment the performance and applicability of the proposed system through the integration of deep learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), which can enhance the system's capacity to extract significant features from CV text.

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