

Integrating Temperament and Personality Traits into Recruitment Frameworks using Adaptive Neuro-Fuzzy Inference system

Samaila Vandi Dia¹, Prof. Gregory Wajiga Modibo¹, Prof. Benson Y. Baha¹

¹ Department of Computer Sciences, Modibo Adama University Yola, Adamawa State, Nigeria

Authors e-mails: samailavandidia@gmail.com, gwejiga@mau.edu.ng, bybaha@gmail.com

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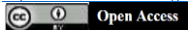
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ABSTRACT

Recruitment decisions continue to rely on structured interviews, academic credentials, and cognitive testing, tools that capture technical competence but consistently overlook the behavioural and dispositional qualities that determine how a new hire actually performs once in role. Decades of organisational research link stable temperament and personality traits to job performance, stress tolerance, teamwork, and retention, yet most intelligent recruitment systems still treat behavioural evaluation as an afterthought. This paper proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS) that integrates applicant temperament, operationalised through the Big Five personality dimensions, with conventional recruitment attributes to produce a continuous, interpretable measure of candidate suitability. Grounded in Trait Theory, Person-Job Fit Theory, and Computational Intelligence Theory, the framework fuzzifies nine input variables, five temperament dimensions and four recruitment attributes, using Gaussian membership functions, and combines them through a first-order Sugeno inference architecture whose rule base is derived through subtractive clustering rather than exhaustive enumeration. A theoretical review of five candidate personality frameworks confirms the Big Five as the most empirically validated and computationally tractable basis for the model, with Conscientiousness and Emotional Stability emerging as the strongest cross-occupational predictors. The resulting nine-input, single-output architecture produces a Job Performance Suitability Index (JPSI) that maps applicants onto four ordinal placement categories. The paper argues that combining the interpretability of fuzzy reasoning with the adaptive learning capacity of neural networks offers a transparent, bias-reducing alternative to both rigid rule-based screening and opaque black-box predictive models, and outlines the training, validation, and comparative evaluation work required to bring the framework to full deployment.

Introduction

Poor hiring decisions impose significant costs on organizations in terms of finance, productivity, morale, and time. Despite advances in human resource management, recruitment remains highly subjective and inconsistent, relying primarily on structured interviews, aptitude tests, academic qualifications, and professional references that often fail to capture important behavioural characteristics influencing workplace performance (Nishad & Singh, 2022; Al-Sultan & Al-Hawari, 2023). Candidates with strong qualifications may still underperform because traditional recruitment methods inadequately assess how individuals respond to pressure, collaborate with colleagues, or adapt to change.

Temperament, defined as the biologically based and relatively stable patterns of emotional response, behaviour, and interpersonal interaction (Rothbart, 2011), plays a significant role in workplace success. Unlike technical skills, temperament is an enduring characteristic that influences how individuals perform within organizational environments. Research consistently demonstrates that traits such as conscientiousness, extraversion, agreeableness, and emotional stability significantly predict job performance, while Person-Environment Fit Theory suggests that employees perform better and experience greater satisfaction when their personal characteristics align with job requirements (Sackett et al., 2021; Kristof-Brown et al., 2005; Nye et al., 2023).

However, temperament data is inherently subjective and imprecise, making it difficult to process using conventional decision-support systems that rely on binary logic (Zadeh, 2021). Fuzzy Logic,

introduced by Zadeh (1965), addresses this limitation by representing behavioural assessments using linguistic variables such as "high," "moderate," and "low," thereby accommodating uncertainty in human judgement. Although fuzzy inference systems improve recruitment decisions, they depend heavily on manually defined membership functions and expert rules, limiting their adaptability (Al-Sultan & Al-Hawari, 2023; García-Crespo et al., 2019). Conversely, artificial neural networks learn directly from data but operate as black-box models, reducing transparency and explainability in recruitment decisions (Bogen & Rieke, 2018).

The Adaptive Neuro-Fuzzy Inference System (ANFIS), proposed by Jang (1993), integrates the learning capability of neural networks with the interpretability of fuzzy logic. ANFIS automatically optimizes membership functions and fuzzy rules from training data, reducing reliance on expert-defined rules while providing transparent and adaptive decision-making (Nayak et al., 2020). These characteristics make ANFIS particularly suitable for recruitment, where inputs are uncertain, behavioural relationships are complex, and decision transparency is essential (Mohammadi et al., 2022).

Despite its advantages, limited research has explored the application of ANFIS specifically for temperament-based candidate evaluation. Existing intelligent recruitment systems largely emphasise measurable qualifications such as education, experience, and technical skills while overlooking psychological and behavioural factors that strongly influence employee retention, teamwork, and long-term performance (Gupta et al., 2022; Nawaz et al., 2023). Consequently, there is a need for an intelligent, data-driven, and psychologically informed recruitment framework capable of processing imprecise temperament information and generating reliable, transparent, and explainable hiring decisions. This study addresses this gap by developing an ANFIS-based recruitment framework that integrates applicant temperament into the employee selection process (Arslankaya, 2023).

2. Literature Review

Understanding the relationship between employee selection, applicant temperament, and organisational outcomes draws on theories from psychology, organizational behaviour, and computational modelling. Employee selection decisions significantly influence organisational effectiveness, and as organizations face increasingly competitive environments and large applicant pools, effective recruitment strategy has become essential to sustaining performance (Meijerink, Bondarouk, & Lepak, 2020). Traditional methods, résumé screening, unstructured interviews, subjective judgment, continue to exhibit bias, inconsistency, and low predictive validity, motivating researchers to explore algorithmic and machine-learning approaches to hiring (Gupta et al., 2022; Alam, Rahman, & Hossain, 2024). Yet even as AI applications in recruitment expand, most systems still rely on historical or behavioural data rather than psychological constructs such as temperament (Nishad & Singh, 2022).

Temperament is one of the oldest conceptualizations of human behavioural tendency, tracing to Hippocrates and Galen's classification of the sanguine, choleric, melancholic, and phlegmatic types, believed to represent innate dispositions shaping emotional reactivity, interpersonal behaviour, and work preference (Keirse, 1998). Modern psychology has reframed these categories through biologically based, continuous models of individual difference (McCrae & Costa, 2008). Despite strong evidence linking temperament to job performance, stress tolerance, teamwork, and occupational fit (Kristof-Brown et al., 2005; Askun, Raghavan, Ajanovic, Çizel, & Wiernik, 2024), computational recruitment systems have largely neglected temperament-based modelling, a critical gap this paper addresses.

2.1 Theoretical Foundations

The proposed framework is based on three complementary theories. **Trait Theory of Personality** views personality as a set of measurable characteristics, with the **Five-Factor Model (Big Five)**—Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism—being the most widely accepted framework for personality assessment (Costa & McCrae, 1992; Goldberg, 1993). Among these traits, **Conscientiousness** and **Emotional Stability** consistently predict job performance, stress management, and career success across different work settings (Sackett et al., 2021; Nye et al., 2023; Duan & Deng, 2023; Askun et al., 2024). Accordingly, Trait Theory provides the basis for selecting temperament variables as inputs to the ANFIS model.

Person–Job Fit (P–J Fit) Theory explains that employee performance depends on the alignment between personal characteristics and job requirements (Kristof-Brown et al., 2005). Better person-job fit leads to improved performance, lower turnover, and greater organisational effectiveness, supporting the

inclusion of temperament traits as key predictors of applicant suitability (Wilmot & Ones, 2021; Bella et al., 2024).

Computational Intelligence and Hybrid Systems Theory provides the technological foundation by combining neural learning with fuzzy reasoning to address uncertainty and nonlinearity (Mendel, 2017). Hybrid neuro-fuzzy systems learn from data, handle imprecise human attributes, and generate interpretable decision rules, justifying the adoption of the **Adaptive Neuro-Fuzzy Inference System (ANFIS)** for transparent and reliable temperament-based recruitment decisions (Nayak et al., 2020; Torra et al., 2022; Kabir & Sumi, 2021).

2.2 From Classical Temperament to the Big Five

The classical **four-temperament model** remains conceptually valuable and aligns closely with the **Big Five** personality dimensions (McCrae & Costa, 2008). Specifically, the **Sanguine** temperament corresponds to high Extraversion and Openness, **Choleric** to high Conscientiousness and moderate Extraversion, **Melancholic** to high Conscientiousness and Neuroticism, and **Phlegmatic** to high Agreeableness and Emotional Stability. This correspondence enables the proposed framework to use the Big Five as its operational input while preserving the interpretive value of the classical model and benefiting from the continuous measurement required for fuzzy inference. Meta-analytic evidence further identifies **Conscientiousness** and **Emotional Stability** as the strongest predictors of job performance, followed by Extraversion, Agreeableness, and Openness (Sackett et al., 2021; Aljuaid, 2026).

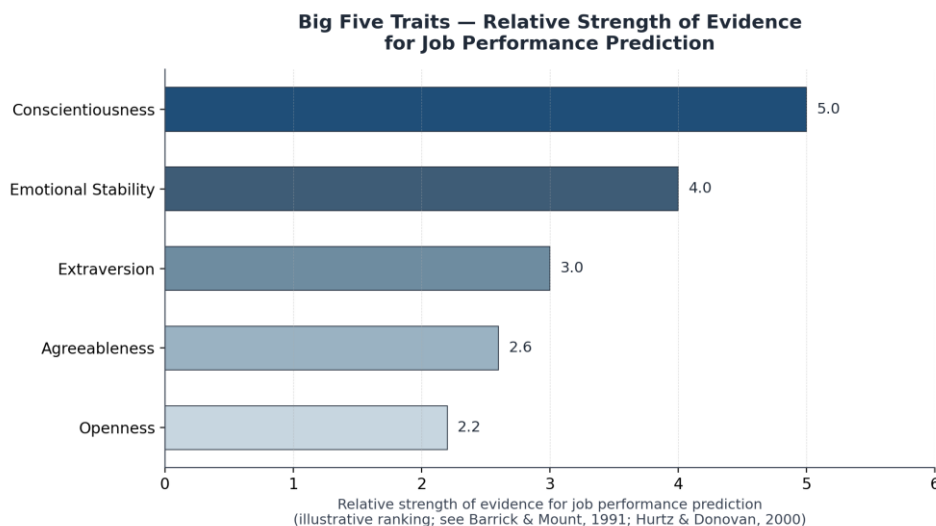


Figure 1. Relative strength of evidence for the Big Five traits in predicting job performance, synthesised from meta-analytic sources (adapted from Sackett et al., 2021; Aljuaid, 2026).

2.3 Temperament in Recruitment: Importance and Challenges

Temperament influences how individuals respond to challenges, interact with others, and perform in the workplace, making it an increasingly important factor in recruitment (Rothbart, 2011). Traits such as conscientiousness and emotional stability are strongly associated with higher job performance, effective stress management, and sustained productivity, while temperament assessment improves person-job fit, employee satisfaction, and retention by aligning behavioural characteristics with job requirements and organizational culture (Sackett et al., 2021; Wilmot & Ones, 2021; Duan & Deng, 2023).

Despite its value, temperament assessment presents several challenges. Differences in theoretical models, cultural variations, and the limitations of self-report and observer-based assessments can reduce measurement accuracy and fairness (Remann & Nordin, 2021; Zhao & Zhang, 2022). Excessive reliance on temperament may also unfairly disadvantage qualified candidates and introduce algorithmic bias if not carefully implemented (Bogen & Rieke, 2018). Therefore, temperament should be used as one component of a comprehensive recruitment framework, supported by appropriate ethical, cultural, and AI governance safeguards rather than as a standalone hiring criterion.

2.4 Integrating Temperament with ANFIS

The **Adaptive Neuro-Fuzzy Inference System (ANFIS)** combines the reasoning capability of fuzzy logic with the adaptive learning ability of artificial neural networks, making it well suited for handling the uncertainty and complexity of human behavioural traits. Unlike conventional models that require precise numerical inputs, ANFIS processes subjective information using fuzzy linguistic variables, enabling effective evaluation of qualitative temperament characteristics (Iwasokun et al., 2022).

In a temperament-based recruitment framework, applicants complete standardized psychometric assessments, whose scores are converted into fuzzy linguistic variables through **fuzzification**. Gaussian membership functions are commonly used because of their smooth transitions and strong learning performance (Sharma & Kaur, 2021). An inference engine applies expert-defined rules, while the neural network component optimizes membership functions and rule parameters using a hybrid learning algorithm that combines gradient descent and least-squares estimation, allowing the model to learn from historical recruitment and performance data (Achmad & Fiqih, 2021; Dutta & Kumar, 2020).

Integrating temperament assessment with ANFIS offers several benefits: it reduces subjective bias through standardized evaluation, effectively manages uncertainty in psychological data using fuzzy reasoning, continuously improves prediction accuracy through adaptive learning, and enhances person-job fit by aligning applicants' temperament profiles with job requirements, thereby supporting improved performance, satisfaction, and employee retention (Kabir & Sumi, 2021; Mohammadi et al., 2022).

3. Methodology

This study adopts a Design Science Research (DSR) approach within a quantitative, model-based research design. DSR is appropriate because the primary outcome is a computational artefact—a temperament-based Adaptive Neuro-Fuzzy Inference System (ANFIS) recruitment decision-support framework—whose effectiveness is demonstrated through its design, development, and empirical evaluation. The DSR process includes problem identification, objective definition, artefact design and development, demonstration, evaluation, and communication of results. The quantitative component involves collecting temperament and job-performance data, training the ANFIS model using a hybrid learning algorithm, and evaluating its predictive performance through k-fold cross-validation and comparative benchmarking.

3.1 Data Requirements

The model requires two categories of data. Applicant temperament data, the primary behavioural inputs, are operationalised through the Big Five personality dimensions, Conscientiousness, Emotional Stability, Extraversion, Agreeableness, and Openness to Experience, each quantified on a 0-100 scale using standardised psychometric instruments (Anastasi & Urbina, 2018), normalised to the interval [0, 1], and mapped to the linguistic terms Low, Medium, and High via Gaussian fuzzy membership functions. Employee selection and placement data provide the empirical foundation for training and validation, comprising demographic information, educational qualifications, work experience, and temperament indicators, with the target output expressed as a continuous Job Performance Suitability Index (JPSI). The combined dataset is partitioned into training, validation, and testing subsets to optimise ANFIS parameters, monitor for overfitting, and evaluate predictive accuracy and robustness respectively.

3.2 Selection of the Temperament Framework

Selection of the specific temperament framework used as ANFIS input followed an explicit evaluation of candidate theories against five criteria: empirical association with job performance, measurability, cross-occupational generalisability, suitability for fuzzification, and non-redundancy. Five frameworks were assessed, the classical Four Temperaments, Eysenck's PEN model, the Five-Factor (Big Five) Model, the Keirsey Temperament Sorter, and Trait Activation Theory. The Big Five was selected as the primary input framework on the strength of its continuous measurability and the depth of recent meta-analytic evidence linking its dimensions, particularly Conscientiousness and Emotional Stability, to job performance across occupations (Sackett et al., 2021; Nye et al., 2023; Aljuaid, 2026), while Trait Activation Theory was retained as the structural rationale explaining how dispositional traits translate into observable performance only when situational cues in the work environment activate them, justifying the framework's approach of matching candidate profiles to role-specific demands rather than applying universal trait thresholds.

3.3 Anfis Architecture

The proposed ANFIS architecture is a nine-input, single-output intelligent inference system that integrates the five Big Five traits with four conventional recruitment attributes, Educational Qualification, Work Experience, Interview Performance Score, and Technical and Professional Skills, to produce a holistic, data-driven suitability prediction. The system implements a first-order Sugeno fuzzy inference system across five layers, fuzzification, rule evaluation, normalisation, defuzzification, and output, chosen for its computational efficiency and suitability for adaptive learning (Jang, 1993). Figure 2 depicts the full five-layer architecture, showing how the nine fuzzified inputs are combined through the rule and normalisation layers into a single defuzzified JPSI output.

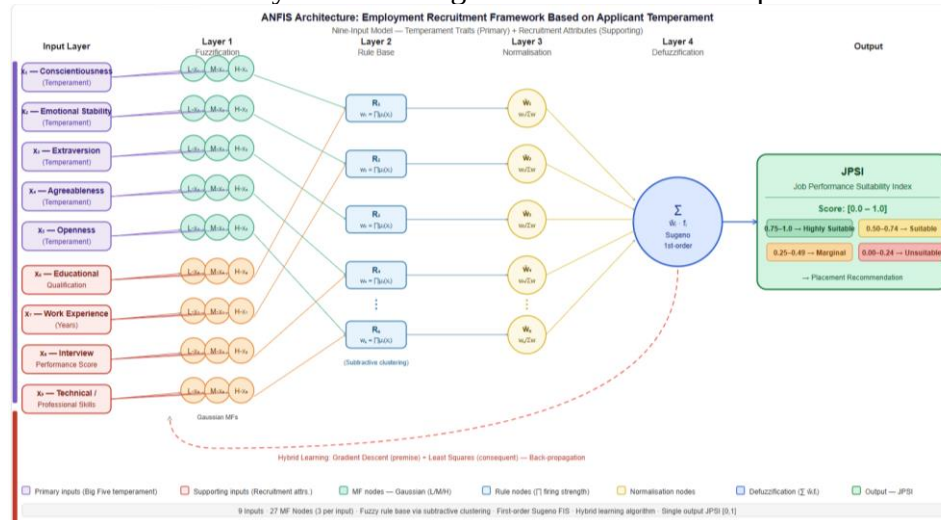


Figure 2. Five-layer ANFIS architecture integrating applicant temperament and personality traits with conventional recruitment attributes for recruitment decision support (design adapted from Jang, 1993).

3.4 Fuzzification and Membership Functions

Each of the nine normalised inputs is fuzzified into three Gaussian membership functions, Low, Medium, and High, yielding twenty-seven membership function nodes in total. Gaussian functions were selected over triangular, trapezoidal, or bell-shaped alternatives on four grounds: they are continuously differentiable across their domain, a property essential for the gradient-descent component of the hybrid learning algorithm; they produce smooth, gradual transitions between linguistic categories that better represent the continuous, overlapping nature of personality trait distributions; their two-parameter formulation (mean and standard deviation) gives the learning algorithm flexibility to independently optimise the location and spread of each curve; and they are widely validated in ANFIS-based human resource applications in the recent literature (Sharma & Kaur, 2021; Dutta & Kumar, 2020). Initial parameter values are established through subtractive clustering applied to the normalised training data, then refined through the gradient-descent backward pass of the hybrid learning algorithm. Figure 3a shows the resulting configuration for the five primary temperament inputs, and Figure 3b shows the corresponding configuration for the four supporting recruitment attributes.

Gaussian Membership Functions — Primary Temperament Inputs (x1-x5)



Figure 3a. Gaussian membership function configuration for the primary temperament inputs (Conscientiousness, Emotional Stability, Extraversion, Agreeableness, Openness).

Gaussian Membership Functions — Supporting Recruitment Inputs (x6-x9)

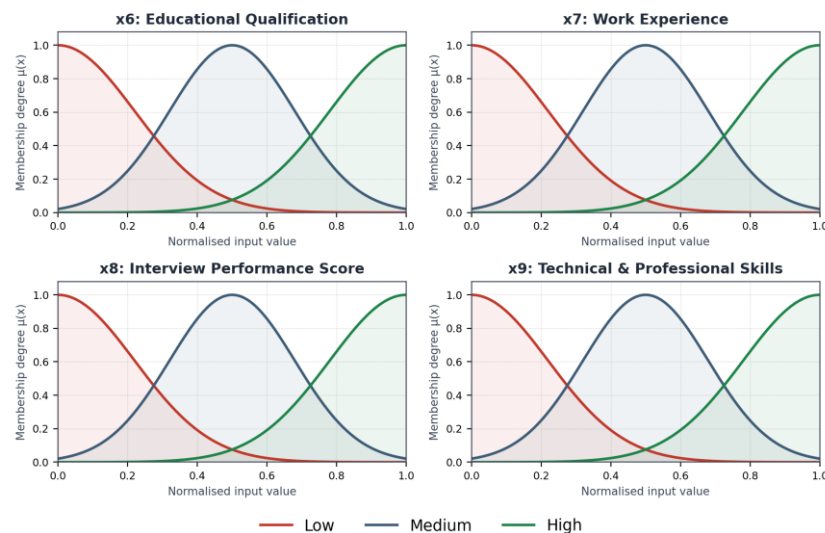


Figure 3b. Gaussian membership function configuration for the supporting recruitment attribute inputs (Educational Qualification, Work Experience, Interview Performance, Technical Skills).

3.5 Fuzzy Rule Base

Given nine inputs each partitioned into three linguistic categories, exhaustive combinatorial enumeration would generate $3^9 = 19,683$ rules, computationally intractable and practically uninterpretable. The rule base is instead generated through subtractive clustering, in which each data point is evaluated as a potential cluster centre based on surrounding data density; the highest-potential points are selected iteratively as cluster centres, and each becomes one fuzzy rule of the form “IF x_1 is A_1 AND x_2 is A_2 AND ... AND x_9 is A_9 THEN $f = p_1x_1 + p_2x_2 + \dots + p_9x_9 + r$ ”, with linear consequent parameters optimised via least-squares estimation. This data-driven approach to rule generation, rather than exhaustive expert enumeration, is consistent with recent applications of neuro-fuzzy systems to personnel evaluation (Kabir & Sumi, 2021; Iwasokun et al., 2022). The resulting rule base is further reviewed by HR professionals and organisational psychologists for validation of linguistic definitions and post-clustering professional coherence, ensuring the final rules are both statistically grounded and practically interpretable. The output, the JPSI, is a continuous score on $[0, 1]$ mapped to four ordinal placement categories, from Unsuitable (0.00-0.24) through Marginal and Suitable to Highly Suitable (0.75-1.00).

4. Results and Discussion

Evaluating the five candidate personality frameworks against the criteria above produced a clear ranking. The classical Four Temperaments and the Keirsey Temperament Sorter operate as categorical rather than continuous systems, limiting their compatibility with fuzzification and computational

modelling despite their historical value. Eysenck's PEN model, though biologically well grounded, offers a narrower three-factor structure whose absence of independent Agreeableness and Openness dimensions restricts its capacity to capture person-job fit for collaborative or creative roles. The Big Five, by contrast, provides continuous, independently validated dimensions with direct meta-analytic links to job performance, Conscientiousness and Emotional Stability showing the strongest cross-occupational predictive validity, complemented by Extraversion, Agreeableness, and Openness in specific role contexts (Sackett et al., 2021; Askun et al., 2024). Trait Activation Theory supplies the contextual bridge explaining when and how these dispositional traits translate into observed performance.

Table 1 summarises the five selected Big Five dimensions and their hypothesised relevance to job performance, informed principally by recent meta-analytic work identifying Conscientiousness as the most robust cross-occupational predictor, with Emotional Stability and, depending on job type, Extraversion and Agreeableness contributing additional predictive value (Sackett et al., 2021; Nye et al., 2023).

Trait	Operational Definition	Hypothesized Relevance to Job Performance
Conscientiousness	Organisation, dependability, goal-directed behaviour	Strongest, most consistent predictor across virtually all occupations
Emotional Stability	Resilience to stress; consistency of mood (inverse of Neuroticism)	Predicts performance under pressure and workplace adaptability
Extraversion	Sociability, assertiveness, interpersonal energy	Strong predictor for sales, management, customer-facing roles
Agreeableness	Cooperativeness, trust, interpersonal warmth	Relevant to team-based and service-oriented roles
Openness to Experience	Intellectual curiosity, creativity, receptiveness to new ideas	Associated with adaptability, training performance, and innovation

Table 2 presents the resulting JPSI score ranges and their corresponding placement categories, translating the continuous output of the neuro-fuzzy model into decision-relevant recommendations for recruitment practitioners.

JPSI Score Range	Placement Category	Interpretation
0.75 - 1.00	Highly Suitable	Strong temperament-role alignment; recommended for immediate placement
0.50 - 0.74	Suitable	Adequate alignment; recommended for placement with minor role adjustments
0.25 - 0.49	Marginal	Partial alignment; recommended for further assessment or alternative role
0.00 - 0.24	Unsuitable	Insufficient alignment; not recommended for the target role

Figure 4 illustrates the practical effect of this configuration for a single representative input variable, showing how a candidate's normalised score maps onto overlapping degrees of Low, Medium, and High membership rather than a single hard category.

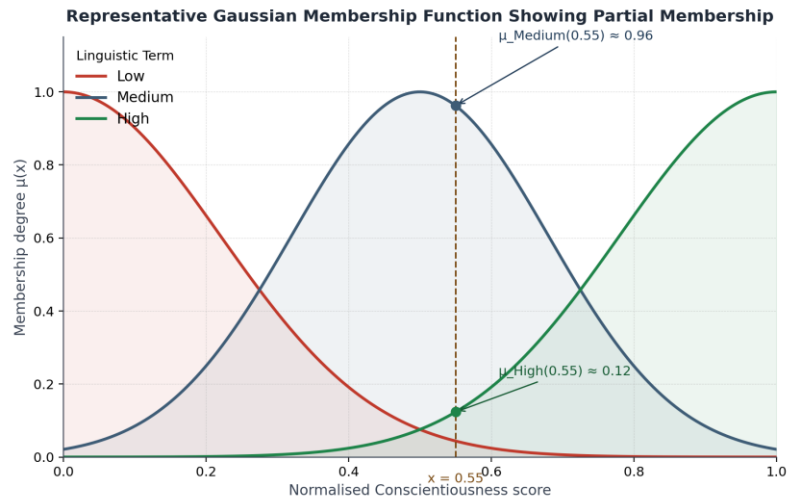


Figure 4. Gaussian membership functions for a representative input variable, showing overlapping Low, Medium, and High regions.

The design of the ANFIS recruitment model produced four key findings. First, the Big Five personality traits provide a continuous and measurable input space compatible with Gaussian membership functions, enabling the system to represent applicants using graded memberships rather than rigid thresholds. For example, a Conscientiousness score of 0.55 can belong simultaneously to the Medium (0.96) and High (0.12) fuzzy sets. Second, the first-order Sugeno ANFIS architecture balances predictive capability with computational efficiency, making it suitable for real-time recruitment decision support (Jang, 1993). Third, the hybrid learning algorithm, combining least-squares estimation and gradient descent, optimizes both fuzzy rules and membership functions from data, reducing reliance on manually defined expert rules (Achmad & Fiqih, 2021). Fourth, subtractive clustering minimizes rule explosion in the nine-input model by generating a compact, interpretable, and learnable rule base (Iwasokun et al., 2022). The resulting model evaluates applicants holistically, producing Job Placement Suitability Index (JPSI) scores ranging from approximately 0.88 (Highly Suitable) for strong profiles to 0.10 (Unsuitable) for weak profiles, rather than relying on any single temperament trait.

5. Conclusion and Future Work

This paper proposed a neuro-fuzzy recruitment framework that integrates applicant temperament into recruitment decision-making. Grounded in Trait Theory, Person–Job Fit Theory, and Computational Intelligence Theory, the framework uses the Big Five personality traits alongside conventional recruitment attributes within a nine-input, single-output ANFIS architecture. Gaussian membership functions and a subtractive-clustering-based rule base enable the system to process imprecise behavioural information while maintaining transparency and interpretability for HR practitioners.

The review identifies the Big Five as the most suitable framework for temperament assessment, with Conscientiousness and Emotional Stability consistently emerging as the strongest predictors of job performance across occupations (Sackett et al., 2021; Nye et al., 2023; Aljuaid, 2026). The classical four-temperament model remains valuable primarily as a conceptual foundation rather than as the primary measurement framework.

Future work will focus on implementing and validating the proposed framework by developing a functional prototype, training and testing the ANFIS model using real recruitment and employee performance data, evaluating predictive accuracy through k-fold cross-validation, and comparing its performance with conventional fuzzy systems and machine-learning approaches (Arslankaya, 2023; Nawaz et al., 2023). Further research should also assess the framework's fairness, transparency, and cultural applicability across diverse populations (Bogen & Rieke, 2018; Remann & Nordin, 2021). With empirical validation, the proposed framework offers a practical, data-driven, psychologically informed, and explainable approach to improving recruitment decision-making.

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