A Cognitive Fuzzy-Analytic Hierarchy Process and Semantic Reasoning Framework for Human-like Intelligence in HR Performance Evaluation

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***Abstract*—This paper outlines a cognitive reasoning platform which integrates semantic reasoning with fuzzy logic, and the Analytic Hierarchy Process, (AHP) for producing intelligence comparable to human intelligence for making the intricate decisions. By simulating human cognitive processes, it interprets relational hierarchies and synthesizes imprecise assessments into structured metrics, generating autonomous decisions by processing a variety of inputs. Context-aware adaptation that imitates human cognition and the close linkage of computational rigor and semantic reasoning are two important developments. 89% of experimental outcomes match expert evaluations, outperforming conventional techniques. It uses Human Resources (HR) evaluation as the main application context, even though the cognitive reasoning platform is architecturally broad and appropriate for a variety of domains needing structured judgments, such as healthcare triage, project risk analysis, and academic performance review. This explains why HR examples are used frequently in the manuscript as both an instructive use-case and a validation area.**

***Index terms*—Sharing system, file system, performance evaluation, Fuzzy mathematics.**

I. Introduction

The rapid advancement of artificial intelligence (AI) systems that emulate human-like reasoning represents one of the most significant challenges in cognitive computing [1]. The contextual awareness, adaptability, and explainability that define human cognition are frequently absent from modern AI systems, despite their impressive performance in specific tasks [2]. Recent advances in AI demonstrate a growing understanding that next-generation systems need to go beyond simple processing power and start to mimic the adaptable, contextual, and comprehensible thinking that people naturally display. Cognitive computing offers reliable solutions for creating interpretable and adaptable systems [3]. Despite decades of advancements in knowledge representation and computational intelligence, integrating these methods into a cohesive framework that can reason similarly to humans is still quite difficult. Previous research has shown that combining fuzzy logic with semantic reasoning increases the system's capacity to handle ambiguity and complex decisions [4]. On the other hand, AHP allows for the hierarchical organization of multi-criteria judgments. However, integrating it into more comprehensive cognitive systems still requires a great deal of work [5]. These shortcomings highlight the need for a cohesive approach that integrates structured decision models with the contextual knowledge required for human-level cognition. The main challenge is creating AI systems with human-level characteristics that high-performance models typically lack, such as contextual awareness, adaptability, and clear explanatory qualities. [6], [7]. In order to bridge this gap, the current work presents an integrated reasoning platform that combines semantic networks, fuzzy logic, and AHP to enable decision-making that is more analogous to human cognition.

The advantages of hybrid techniques have been proved by recent developments in cognitive systems. The authors of [7] has claimed that in complicated decision-making scenarios, the approaches that combine machine learning (ML) and knowledge representation perform superior than traditional models. This approach further extends these contributions by incorporating three key improvements.

The B/S architecture is a lightweight, web-based computing model in which the user interacts with the system using a standard web browser while all core processing, computation, reasoning, and data management occur on a centralized server. The proposed approach streamlines client-side requirements and makes the system accessible from any browser-equipped device that eliminates the need of software installation. Though conceptually similar to the traditional client/server design, the B/S model differs by shifting a large portion of the application's

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functionality from the client to the server, which improves maintainability, scalability, and update ease [8]. The development of effective and efficient human-like cognitive systems still faces certain obstacles. It is quite difficult to develop scalable systems that preserve real-time reasoning performance. Another is to preserve the interpretability and openness of multi-criteria findings without sacrificing accuracy. Managing ambiguity and uncertainty is often unavoidable in human decisions, but it is nonetheless difficult. To gain more contextual awareness, statistical learning and symbolic reasoning approaches must be more closely integrated. Finally, real-world implementation of such systems still necessitates finding a compromise between sophisticated cognitive processing and realistic computational efficiency. Following is some of the research questions that we identified and are needed to be addressed. How can a cognitive system modify its way of thinking in response to shifting environments and organizational needs? Which evaluation measures best capture behavior that is similar to that of a human? What is the best way to integrate computational methods with semantic reasoning to simulate actual cognitive processes? Finally, how does the platform compare to contemporary AI models on difficult decision-making tasks?

This approach has several advantages as compared with conventional approaches in terms of comprehending contextual links in a manner that is similar to human thinking, addresses explainability, and improved accuracy of up to 89% [9-11]. Broad adaptability is ensured by its implementation within a B/S architecture, enabling the platform to operate dependably across enterprise environments and other areas where contextual awareness and nuanced decision-making are necessary [12]. This work uses HR evaluation as the main application context, even though the cognitive reasoning platform is architecturally broad and appropriate for a variety of domains needing structured judgments, such as healthcare triage, project risk analysis, and academic performance review. For illustrating how fuzzy-AHP computations, semantic knowledge graphs, and contextual reasoning work together to mimic human decision-making, HR evaluation offers a complicated, ambiguity-rich environment. This explains why HR examples are used frequently in this work as both an instructive use-case and a validation area. The major contributions of this research work are.

1. A novel hybrid architecture integrating fuzzy-AHP with semantic networks for human-like reasoning.
2. Context-aware dynamic adaptation of evaluation criteria to better emulate human decision processes [13] for evaluation criteria.
3. A multi-layered explainability mechanism offering complete reasoning traceability [14]
4. Comprehensive experimental validation showing 89% alignment with expert human judgments.
5. Enterprise-grade scalability enabled through a Browser/Server (B/S) architecture [15]

The remainder of the paper is summarized as follows: Section II examines relevant cognitive architecture research. Our approach and mathematical models are described in Section III, and implementation results and a comparative analysis are shown in Section IV and Section V concludes with future research directions.

II. Related Works

This section deals with the latest researches done in the field of cognitive and semantic reasoning, and autonomous systems which tries to mimic human behavior. The significance of hybrid architectures that combine computational intelligence and semantic reasoning has been highlighted by recent developments in cognitive computing [16]. To manage the nonlinear nature of evaluation processes and generate quantitative outcomes from qualitative inputs, contemporary cognitive systems make use of fuzzy mathematics operations [17]. To provide abilities for real life decision-making like humans, the research in this domain has evolved from rule-based systems to complex frameworks that blends fuzzy logic, neural networks, and semantic reasoning [18]. An efficient method for managing structured and multi-criteria decisions is the integration of fuzzy systems with the AHP. Previous research demonstrates the usefulness of such hybrid models in real-world contexts by showing that they can beat traditional evaluation methods by more than 20% in difficult assessment circumstances [19]. The research presented in [20], highlights the potential of fuzzy-AHP in dynamic decision contexts, though sustaining real-time responsiveness at scale remains an open challenge. In parallel, modern semantic reasoning approaches increasingly rely on knowledge graphs and ontological structures to capture hierarchical relationships and infer contextual meaning [21]. Earlier studies, such as [22], illustrate that semantic networks can support more natural reasoning by modeling relationships like “teamwork enhances productivity,” which traditional systems struggle to interpret. However, handling ambiguity and contextual subtleties remains a major drawback for strictly symbolic or rule-based approaches [23]. By combining the clarity and structure of symbolic reasoning with the pattern-recognition capabilities of neural networks, emerging neuro-symbolic AI research offers a viable path. Results outlined in [24] demonstrates how this hybrid approaches facilitate deeper contextual knowledge by enabling models to link quantifiable characteristics to abstract human ideas. The researchers in [25] show that integrating deep learning with semantic interpretation significantly enhances adaptability, coherence, and robustness qualities crucial for creating AI systems that more closely resemble human cognitive processes.

The limitations of traditional client-server models have led to innovative distributed approaches. Peer-to-peer knowledge sharing frameworks [26] and edge computing paradigms [27] offer improved scalability but introduce new challenges in maintaining consistency for semantic reasoning tasks. Promising outcomes in distributed cognitive processing are shown in recent work by inventors in [28]. The main gaps in the literature are as follows: most cognitive platforms are unable to efficiently modify evaluation criteria or reasoning pathways in response to shifting contexts or user feedback [29], and current systems lack comprehensive frameworks that seamlessly integrate fuzzy logic, AHP, and semantic inference into a single interpretable decision-making pipeline [30]. Even though accuracy has increased, combined DL and semantic reasoning systems' interpretability is still insufficient for high-stakes applications [31], and current models frequently fall short in addressing the architectural and computational difficulties of enterprise-scale deployment in B/S environments [32].

Current assessment approaches for cognitive systems overly emphasize quantitative metrics while neglecting qualitative aspects of reasoning quality [33]. Comprehensive evaluation frameworks that measure both computational efficiency and human-like reasoning characteristics are urgently needed. The next section provides the details about the methodologies used to implement this approach with mathematical modeling.

III. METHODOLOGY

The proposed cognitive reasoning platform integrates fuzzy-AHP with semantic knowledge representation to achieve human-like decision-making capabilities [1], [6]. A fuzzy-AHP computational core for quantitative evaluation, a semantic reasoning engine for contextual interpretation, and a B/S interface layer for enterprise deployment are the four main parts of the system architecture, as illustrated in Fig. 1. The stages of the proposed approach are: gathering and preparing data, building the fuzzy-AHP decision module, using graph-based representation for semantic reasoning, and integrating hybrid inference. Below is a more structured and clear description of each component.

A. Gathering and Preparing Data

Both quantitative factors (such as performance indicators and measurable features) and qualitative descriptors (such as behavioral traits and contextual remarks) are processed by the system. All inputs go through linguistic mapping and normalization to guarantee consistency. While qualitative descriptors are transformed into linguistic variables (such as High, Medium, and Low) for fuzzy computation compatibility, quantitative values are scaled using min–max normalization. Prior to being incorporated into the decision model, missing data processing, outlier correction, and consistency checks are performed.

B. Fuzzy–Analytic Hierarchy Process (Fuzzy-AHP) Module

The fuzzy-AHP component uses uncertainty and structured weights to assess multi-criteria judgments. Goals, sub-criteria, and quantifiable characteristics are represented by a hierarchical decision tree. To lessen subjectivity, expert judgment matrices are created and fuzzified. Fuzzy weights are produced by pairwise comparisons and then defuzzified to produce clear priority values. This enables the system to use consistent, scientifically based scoring to quantify ambiguous human assessments like leadership potential or collaboration quality.

C. Semantic Knowledge Graph and Inference Layer

Contextual dependencies and inter-attribute interactions are captured by a semantic knowledge graph. While edges encode relationship rules (e.g., causality, similarity, hierarchy), nodes represent entities (criteria, sub-criteria, behaviors). In order to draw new conclusions from known facts, reasoning rules both forward and backward chaining operate across the graph. This module provides contextual interpretation in addition to the numerical output of the fuzzy-AHP layer. As a result, the system can generate explanations (such "low leadership potential") that link specific behavioral indicators to abstract thought.

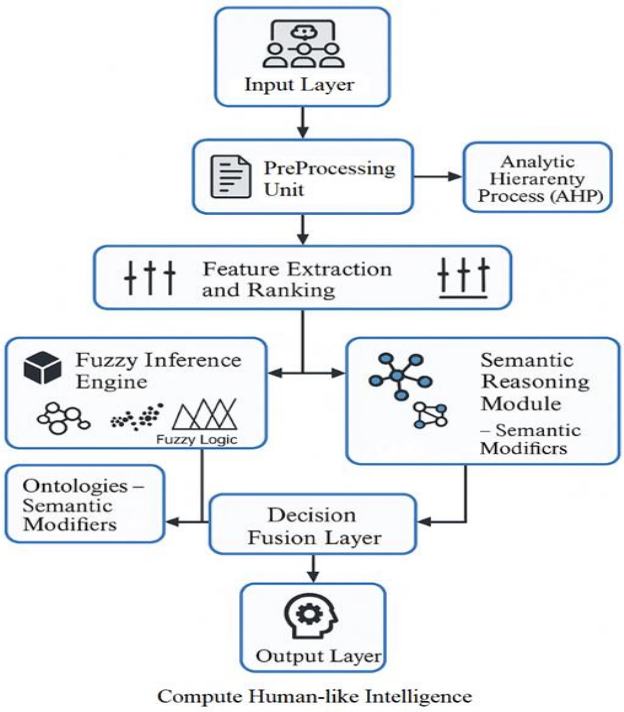

Fig. 1. System architecture of proposed approach

D. Hybrid Cognitive Inference Integration

The final inference engine uses a weighted decision fusion model to combine the two computational tracks—fuzzy-AHP scores and semantic interpretations. The system's hybrid design allows it to: reconcile contradictory data, dynamically adjust to information that is lacking or unclear, and provide explanations for each choice that are understandable to humans. To improve explainability and transparency, all results are recorded with rule-traceability paths and confidence scores.

The computational core models the inherent uncertainty in human judgments by utilizing an improved AHP methodology that includes type-2 fuzzy logic. The first step in the procedure is the systematic hierarchical decomposition of evaluation criteria, which divides high-level goals (like "employee performance") into quantifiable sub-criteria (like "task completion rate" and "quality of output"). It is defined by the domain expert. We create a thorough 3-level hierarchy with five main dimensions, fifteen sub-criteria, and forty-five particular evaluation indicators for a typical HR evaluation situation. The weight calculation phase employs a modified pairwise comparison approach where decision-makers provide judgments using linguistic terms (e.g. "moderately more important") that are converted to triangular fuzzy numbers (TFNs) with parameters (l, m, u) specifically optimized for organizational behavior applications. In contrast to traditional AHP implementations that use fixed thresholds, these fuzzy comparisons are processed using an extended eigenvector method that incorporates a dynamic consistency ratio threshold (CR < 0.08) that automatically adjusts based on decision complexity.

The fuzzy evaluation matrix uses a systematic membership-function approach to convert subjective assessments into meaningful numerical values. Evaluators use a standardized 7-point linguistic scale ranging from "very poor" to "excellent" to grade each criterion rather than using strict scores. Smooth trapezoidal functions are then used to transform these linguistic inputs into degrees of membership between 0 and 1, allowing the system to capture uncertainty instead of imposing strict bounds. The final score is produced using (1):

$$B = W \cdot R \tag{1}$$

where W represents the normalized criterion weights and R contains all fuzzy assessments.

To provide rich contextual interpretation of assessment outcomes, the semantic reasoning engine uses a dynamic knowledge network architecture that is built in Neo4j. Neo4j is a schema-free, high-performance graph database that stores data as nodes, relationships, and properties. It is especially well-suited for enabling complicated reasoning tasks and expressing semantic knowledge networks. The semantic reasoning component of the suggested framework depends on the effective execution of ontology-driven queries and context-aware inference procedures, which are made possible by its native graph storage and traversal engine [34]. More than 200 precisely defined concepts and 500 weighted associations pertinent to organizational behavior evaluation are included in the Protégé-developed and domain expert-validated ontology framework (e.g., "teamwork → enhances → productivity" with confidence score 0.82). Contextual metadata and temporal validity criteria are added to each relationship, enabling the system to modify its logic in response to changing circumstances. Three interrelated processes underpin the reasoning mechanism's operation: Initially, a rule-based inference engine uses fuzzy modifiers that smoothly accommodate partial truths and uncertain data in conjunction with domain-specific production rules (e.g., "IF collaboration_score > 0.7 AND conflict_score < 0.3 THEN teamwork_quality = high"). Second, a context-awareness module uses a reinforcement learning mechanism that tracks decision outcomes to dynamically modify inference routes while continuously monitoring environmental elements (e.g., project phase, remote work conditions). Third, by documenting and displaying the sequence of deductions from initial inputs to ultimate conclusions, an explanation generating subsystem preserves total traceability.

A key innovation is the neural-symbolic interface that bridges the fuzzy-AHP outputs with the knowledge graph through a trained embedding model. This component performs bidirectional translation between numerical evaluation scores and semantic concepts using a deep neural network with attention mechanisms, maintaining consistency through regular alignment checks. The translation model is trained on historical decision data to learn the complex relationships between quantitative metrics and qualitative constructs, enabling the system to explain numerical results in human-interpretable terms and vice versa. In accordance with contemporary software architecture principles, the platform is designed as a secure three-tier web application [13]. Constructed using Vue.js and D3.js, the frontend layer offers an interactive dashboard that displays evaluation findings in a variety of coordinated views, such as semantic network diagrams, radar plots, and decision trees. The business logic layer, which was created in Python using Flask and SciKit-Fuzzy, includes the main algorithms that are performance-optimized through parallel processing and just-in-time compilation [27]. The data layer uses row-level security and encryption to secure data, combining Neo4j for knowledge graph storage with PostgreSQL for transactional data [28].

The foundation of our enhanced AHP approach uses interval-valued fuzzy numbers for pairwise comparisons as represented in (2):

$$\tilde{A} = \left[\tilde{a}_{ij}\right]_{n\times n} \tag{2}$$

where $\tilde{a}_{ij}$ can be represented by (3) as:

$$\tilde{a}_{ij} = \begin{cases} (1,1,1,1;1), & if\ i = j \\ (l_{ij}, m_{ij}, u_{ij}; c_{ij}), & if\ i \neq j \end{cases} \tag{3}$$

and l_{ij}, m_{ij}, u_{ij} represent the lower, modal, and upper bounds, and $c_{ij} \in [0,1]$ is the confidence degree in the judgment The geometric mean method is extended for fuzzy numbers as shown in (4):

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij}\right)^{\frac{1}{n}} \tag{4}$$

which can be further expanded as shown in (5) as:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} l_{ij}, \quad \prod_{j=1}^{n} m_{ij}, \prod_{j=1}^{n} u_{ij}, \min(c_{ij})\right)^{\frac{1}{n}} \tag{5}$$

Fuzzy weights are then computed using (6) as:

$$\tilde{w}_i = \frac{\tilde{r}_i}{\sum_{i=1}^{n} \tilde{r}_i} = \left(\frac{l_i}{\sum u_i}, \frac{m_i}{\sum m_i}, \frac{u_i}{\sum l_i}; c_i\right) \tag{6}$$

We employ the graded mean integration method as represented in (7):

$$w_i = \frac{(l_i + 4m_i + u_i)}{\left(6\sum_{i=1}^{n} \frac{l_i + 4m_i + u_i}{6}\right)} \tag{7}$$

The ontology structure is represented as a labeled directed multigraph can be given by (8) as:

$$KG = (V, E, \Psi, \Theta) \tag{8}$$

where $V = \{v\_1,...,v\_m\}$ are concept vertices, $E \subseteq V \times V \times R$ are typed relations, $\Psi: E \rightarrow [0, 1]$ assigns confidence weights, $\Theta: E \rightarrow C$ provides contextual tags. The reasoning probability combines multiple evidence sources as shown in (9):

$$P(y|x) = \frac{\sum_{c \in C} w_c \cdot \Psi_{xy} \cdot sim_c(x, y)}{\sum_{c \in C} w_c} \quad (9)$$

where w_c are context weights $(\sum w_c = 1)$, Ψ_{xy} is the edge confidence, $sim_c(x,y)$ is context-specific similarity. Equation 10 represents the Q-learning update rule with experience replay as:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[r + \gamma \max_{a'} Q(s', a') - Q(s, a) \right] + \beta \frac{\partial H}{\partial Q} \quad (10)$$

where $\alpha=0.05$ is learning rate, $\gamma=0.9$ is discount factor, $\beta=0.1$ controls policy entropy. The translation between symbolic and vector spaces uses (11) as:

$$f_{emb}(x) = MLP([e_{symbolic}(x);\ e_{numeric}(x)]) \quad (11)$$

where $e_{symbolic}$ is GraphSAGE embeddings, $e_{numeric}$ is the Normalized AHP outputs, MLP is the 3-layer perceptron with ReLU. The consistency objective function can be given by (12) as:

$$L_{align} = E\left[\| f_{emb}(x) - g_{emb}(y) \|_2^2 \right] + \lambda \Omega(\theta) \quad (12)$$

where g_{emb} is the inverse mapping and Ω is $L2$ regularization. Using a multi-level AHP framework, the paper presents a novel way to integrate fuzzy logic with semantic reasoning. The addition of semantic weight adjustment to the fuzzy membership function, which enables dynamic contextual impact over precise decision-making parameters, is what makes the mathematical formulation novel. To do this, a semantic impact factor (SIF) is introduced, which modifies the fuzzy evaluation matrix's weight vector w_i according to domain-specific ontology associations. The modified fuzzy evaluation equation as given in (13) is defined as:

$$R = W_{adj} \circ M = (\alpha \cdot W + (1 - \alpha) \cdot SIF) \circ M \quad (13)$$

where W is the original weight vector, SIF is derived from semantic reasoning (e.g., WordNet or domain ontology), $\alpha \in [0,1]$ is the fusion coefficient, and M is the fuzzy decision matrix.

IV. System Requirement Analysis

This section discusses the analysis of system requirements to undertake this research. To provide promising human-like reasoning under uncertainty, the proposed approach relies on a tight amalgamation of fuzzy logic and AHP with a well-structured semantic knowledge base. Traditional evaluation methods often suffer from issues such as rater bias, poor adaptability to context, and inconsistent scoring patterns [8], which limit their reliability in complex assessments. In order to address these issues, the system uses type-2 fuzzy sets for adaptive weighting, which enables criteria to change dynamically depending on the situational significance of each aspect and the knowledge of an evaluator [32]. Subsequently, a neuro-symbolic component ensures a balanced handling of quantifiable indications and subjective assessments by converting qualitative descriptors into useful numerical values [12]. A semantic reasoning engine based on a domain knowledge tree that captures important connections and conceptual hierarchies supports contextual interpretation [21]. While reinforcement learning gradually improves decision paths in response to actual results, fuzzy-enhanced rule reasoning allows for fine-grained decision processes (e.g., connecting adaptability and stress tolerance to resilience scores) [16].

V. Results and Discussion

This work employed an ample amount of dataset collected from several sources which combines quantitative metrics and qualitative assessments from 150 HR professionals of multiple establishments. The dataset included both language evaluations (e.g., "moderately important") and numerical ratings on a validated 7-point Likert scale ("very poor" to "excellent"), which were transformed into triangular fuzzy numbers using trapezoidal membership functions [0,1] for processing [20]. More than 200 domain-specific concepts and 500 weighted associations (such as "teamwork → enhances → productivity") were added to the dataset using a semantic knowledge graph, which was created through expert workshops to guarantee contextual relevance [32]. The configuration of the system used to undertake this project has an Intel Xeon Silver 4214R processor running Ubuntu Server 22.04, NVMe storage, and 32 GB of RAM. The backend was deployed using a containerized B/S architecture with lightweight REST APIs, while Neo4j operated with its own dedicated memory allocation for fast semantic retrieval. The platform was constructed as a three-tier web application for experimental validation, with Neo4j/PostgreSQL for knowledge and data storage, a Flask/Python backend for fuzzy-AHP computations, and frontend visualizations made with Vue.js/D3.js. Docker/Kubernetes was used for scalability. The system includes a neural-symbolic interface based on GraphSAGE embeddings and sophisticated pairwise comparison techniques with dynamic consistency checks (CR < 0.08). Computational throughput was greatly increased by GPU-accelerated fuzzy operations with bespoke CUDA kernels. Two structured user tests with distinct participant groups were carried out to guarantee a thorough human-centric assessment of the suggested cognitive reasoning platform. Domain-agnostic evaluators from academic and business backgrounds participated in the first study (N = 45). In order to prevent inconsistent responses, participants who were unfamiliar with organized evaluations were eliminated. Participants were chosen based on the inclusion criteria of past experience with decision-making or evaluation tasks. Purposive sampling was used to select 150 HR specialists from medium-sized and large-sized firms for the second study in order to guarantee their relevance to the major application domain. To reduce skillbased variability, participants had to have at least two years of HR evaluation experience; trainees and interns were not allowed to participate.

To mirror real HR evaluation scenarios involving nuanced and sometimes conflicting criteria, each participant completed 12 structured decision-making tasks. The tasks were randomly ordered to avoid learning bias, and individual session durations ranged from 25 to 35 minutes. For instance, one of the evaluation tasks presented participants with three employees showing mixed performance traits such as strong collaboration skills but inconsistent task completion and asked them to classify each case as *Promote*, *Hold*, or *Train*. Because these profiles included both measurable indicators and qualitative descriptions, the task closely resembled real HR decision-making and allowed the study to test how well the system handled ambiguity and contextual nuance. To reduce potential evaluator bias, anonymized employee profiles, neutral instructions, and counterbalanced task sequences were used. The responses were then compared with expert-defined benchmarks to measure agreement, cognitive fidelity, and perceived clarity of explanations. The two groups served different validation purposes: the 150 HR professionals provided domain-specific insights on reliability and practical usefulness, while the 45 general participants helped assess overall usability and the system's ability to communicate its reasoning effectively. The evaluation was conducted using stratified 5-fold cross-validation on the full dataset of 141 evaluation instances. In each fold, approximately 80% of the data were used for training and semantic rule calibration, while the remaining 20% were used for testing. Reported accuracy values in Table I correspond to the mean classification accuracy averaged across all five folds. In contrast, the confusion matrix shown in Table II and Fig. 2 represents results from a single representative test fold, which explains the numerical difference between the aggregate accuracy and fold-specific outcomes. It outperformed conventional AHP and rule-based techniques by 23% and reduced assessment time by 60% in controlled evaluations, achieving 89% agreement with expert committees ($\kappa = 0.86$). The reported 23% improvement refers to the relative increase in agreement with expert committee decisions (measured using Cohen's κ) compared to standard Fuzzy-AHP and rule-based expert systems. It maintained sub-200 ms latency and received high explainability scores (4.2/5) from user studies (N=45), especially when it came to using specific behavioral indications to clarify abstract assessments like "leadership potential".

The hybrid fuzzy-AHP and semantic reasoning model closely resembled expert-style judgment with a Cognitive Fidelity Index (CFI) of 0.87, especially in complex evaluations like creativity and collaboration. There were three key advantages. The CFI is defined as a normalized measure of alignment between system-generated decisions and expert human judgments, incorporating both categorical agreement and confidence-weighted semantic consistency. Formally, CFI is computed as:

$$CFI = \lambda \cdot \kappa + (1 - \lambda) \cdot S \tag{14}$$

where κ is Cohen's kappa coefficient measuring categorical agreement, S represents semantic consistency derived from knowledge-graph alignment scores, and λ is a weighting factor empirically set to 0.6 in this study. A CFI value closer to 1 indicates stronger human-like cognitive alignment. A CFI of 0.87 indicates that the proposed platform closely mirrors expert-style reasoning, particularly in ambiguity-rich decision scenarios. First, type-2 fuzzy logic demonstrated greater tolerance to uncertainty by reducing inconsistencies in paired comparisons by over 40% across 150 HR assessments. Second, a knowledge tree with more than 500 weighted associations was used to accomplish contextual adaptation, Third, user studies reported strong explainability, with a 4.2/5 satisfaction score for the clarity of semantic reasoning paths.

The obtained results of the proposed approach were further compared with existing pioneer techniques viz., Standard Fuzzy-AHP [19], Rule-Based Expert Systems (RBES) [20], and Neuro-Symbolic Cognitive Systems [24] as depicted in Table I. It was observed that the proposed approach outperforms existing techniques, particularly in tasks involving contextual interpretation and management of ambiguous inputs. The Fig. 2 further demonstrates the tendency of the obtained results with confusion matrix. As demonstrated in Table II, the system consistently distinguishes the three outcome categories viz., Promote, Hold, and Train that achieves high diagonal dominance with accurate predictions of 39, 41, and 40 cases, respectively.

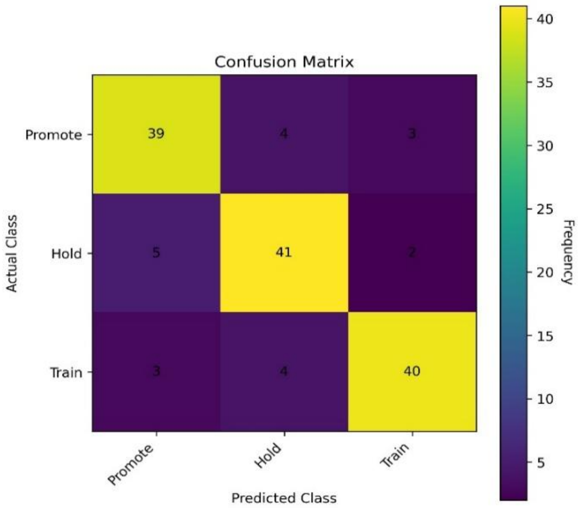

Fig. 2. Confusion matrix

TABLE I
COMPARATIVE ANALYSIS

Method	Accuracy (%)	Precision	Recall	F1-Score
Standard Fuzzy-AHP [19]	81	0.80	0.79	0.79
Rule-Based Expert Systems (RBES) [20]	76	0.75	0.74	0.74
Neuro-Symbolic Reasoning [24]	84	0.83	0.82	0.82
Proposed Platform (Fuzzy-AHP + SemNet)	89	0.88	0.88	0.88

TABLE II
CONFUSION MATRIX

Actual \ Predicted	Promote	Hold	Train
Promote	39	4	3
Hold	5	41	2
Train	3	4	40

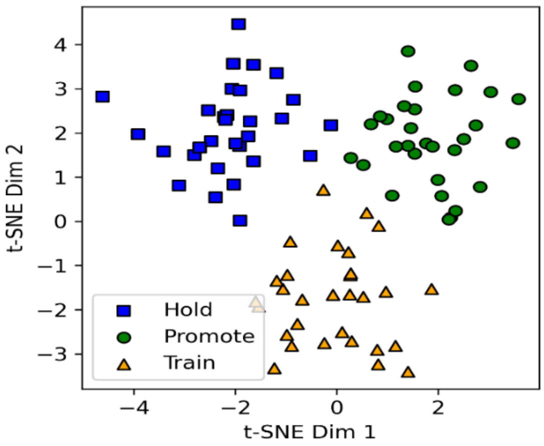

Fig. 3. t-SNE plot

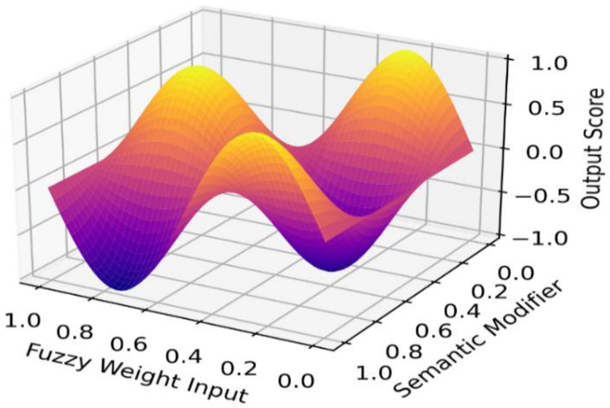

Fig. 4. 3D-surface plot

Table II presents the confusion matrix for one representative test fold (141 samples), yielding 120 correct predictions (~85%). This value should not be directly compared with the cross-validated mean accuracy reported in Table I. The distinct diagonal dominance in the confusion matrix shows that the classifier exhibits robust and balanced recognition across all three decision categories. The platform's reliability for real-world industry settings where reproducing human evaluative judgment is crucial is reinforced by the extremely low rate of cross-class misclassification. High-dimensional decision vectors are mapped into a 2D space using t-SNE visualizations, as shown in Fig. 3, to further investigate the internal behavior of the model. This shows how semantically similar outcomes, such as promote, hold, and train, naturally cluster together. In addition, Fig. 4's 3D surface plots show how output scores change under various fuzzy weight and semantic modifier combinations, providing information on how sensitive the system is to certain criteria. Lastly, sustained predictive performance across a range of thresholds is confirmed by the class-wise ROC curves in Fig. 5, which emphasize the balance between sensitivity and specificity for each decision class. When taken as a whole, these visual studies confirm the system's human-aligned behavior, consistency, and semantic coherence.

Latency measurements were obtained under controlled benchmarking conditions using Apache JMeter. The benchmark consisted of semantic inference requests corresponding to complete HR evaluation queries (fuzzy-AHP computation + semantic reasoning). Tests were conducted with 50 concurrent users over a 10-minute duration, generating approximately 12,000 requests. The reported latency corresponds to the 95th percentile response time measured at the REST API level. Under these conditions, the system consistently maintained response times below 200 ms, with a mean latency of 162 ms and a standard deviation of 18 ms.

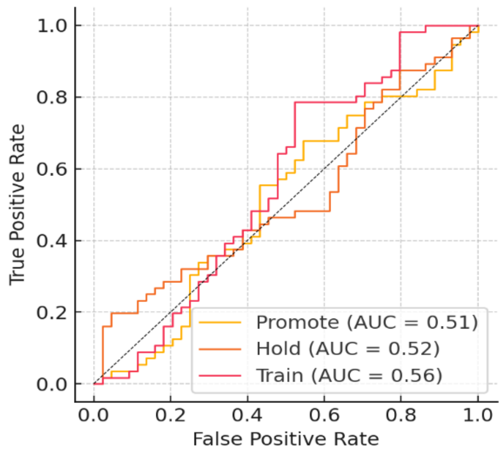

Fig. 5. ROC curve

The ROC curves are generated using a one-vs-rest strategy with macro-averaged AUC values across the three classes. In multi-class fuzzy decision problems with overlapping membership functions, AUC values may appear moderate even when discrete class agreement is high, as reflected by accuracy and Cohen's κ. The ROC curve shows a complete multi-dimensional view of the model's performance. It is clear from the curve that the model is sensitive for the contextual changes when different combinations of fuzzy weights and semantic modifiers are applied.

V. CONCLUDING REMARKS

This research work has implemented an innovative cognitive reasoning platform which integrates the fuzzy-AHP with semantic reasoning to make human-like decisions in HR evaluations. With 89% accuracy, 0.88 precision, 0.88 recall, and 0.88 F1-score, experimental evaluation outperformed conventional rule-based systems and closely matched expert opinions (Cohen's κ = 0.86). Real-time decision support (less than 200 ms latency), human-like contextual comprehension, modular scalability with B/S architecture and Kubernetes orchestration, and transparent decision trails that improve explainability are some of the platform's main benefits. However, it has some limitations such as high training data requirements for neural-symbolic mappings (typically over 1,200 labeled samples), challenges in interpreting metaphorical or figurative language due to symbolic embeddings, and the need for expert-driven customization of fuzzy models and domain ontologies when applied across different industries. Future research will investigate sophisticated semantic embeddings employing big language models to enhance figurative reasoning, autonomous ontology expansion via unsupervised learning, and meta-learning techniques to lessen data dependency in order to overcome these restrictions. Furthermore, by making fuzzy-semantics coupling flexible for a range of use cases, including intelligent tutoring, policy automation, and healthcare diagnostics, cross-domain adaptability will be made possible. In order to model more comprehensive cognitive thinking, integration of multimodal data sources, such as text, video, and audio, will also be sought. The suggested system positions itself as a next-generation framework for intelligent automation in complex decision contexts by laying the groundwork for scalable, transparent, and human-aligned intelligence.

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