Design of an Intelligent Military Recruitment Support System Based on Certainty Factor and Forward Chaining Inference

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Military recruitment demands careful evaluation across multiple dimensions, including administrative eligibility, physical fitness, cognitive ability, and psychological readiness. This paper presents the development of an intelligent decision support system (DSS) designed to assist and enhance recruitment decisions in the military sector. Leveraging a rule-based expert system, the DSS applies the Certainty Factor (CF) model to manage uncertainty and combines it with a Forward Chaining inference mechanism for explainable reasoning. The system was built with guidance from military domain experts and tested through simulations using 20 candidate profiles. Results indicate strong alignment with human expert judgment, achieving 87% accuracy and delivering transparent recommendations based on structured rules and confidence scores. Unlike conventional black-box models, the DSS offers full traceability for each decision made, ensuring accountability and consistency-qualities essential in defense-related processes. Beyond its current capabilities, the system is designed to be scalable and adaptable. It can accommodate evolving recruitment policies and integrate additional evaluation criteria, such as biometric data. Although current CF weights rely on expert input, future development may involve dynamic rule optimization through machine learning or feedback mechanisms. In conclusion, the proposed DSS serves as a practical and explainable tool that bridges expert knowledge with intelligent automation. It offers a forward-looking approach to improving fairness, efficiency, and transparency in military

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***Abstract*—Military recruitment demands careful evaluation across multiple dimensions, including administrative eligibility, physical fitness, cognitive ability, and psychological readiness. This paper presents the development of an intelligent decision support system (DSS) designed to assist and enhance recruitment decisions in the military sector. Leveraging a rule-based expert system, the DSS applies the Certainty Factor (CF) model to manage uncertainty and combines it with a Forward Chaining inference mechanism for explainable reasoning. The system was built with guidance from military domain experts and tested through simulations using 20 candidate profiles. Results indicate strong alignment with human expert judgment, achieving 87% accuracy and delivering transparent recommendations based on structured rules and confidence scores. Unlike conventional black-box models, the DSS offers full traceability for each decision made, ensuring accountability and consistency-qualities essential in defense-related processes. Beyond its current capabilities, the system is designed to be scalable and adaptable. It can accommodate evolving recruitment policies and integrate additional evaluation criteria, such as biometric data. Although current CF weights rely on expert input, future development may involve dynamic rule optimization through machine learning or feedback mechanisms. In conclusion, the proposed DSS serves as a practical and explainable tool that bridges expert knowledge with intelligent automation. It offers a forward-looking approach to improving fairness, efficiency, and transparency in military recruitment processes.**

Keywords—Military recruitment, decision support system, Fuzzy, TNI, expert system

I. INTRODUCTION

Military recruitment is not merely a selection process but a strategic filtration mechanism that determines the operational integrity of national defense [1]. The selection must incorporate multifactorial assessments involving administrative accuracy, physical endurance, psychological stability, and ideological alignment with national principles [2]. However, in practice, these components are often evaluated independently, leading to fragmented decision-making that may overlook nuanced candidate profiles [3]. The consequences of poor recruitment decisions are profound, ranging from inefficiencies in training investments to compromised mission readiness [4].

While automated systems have been widely adopted in civilian human resource management, their adoption in military settings remains limited [5]. This gap is primarily due to the unique constraints in military recruitment, such as legal compliance with national defense policies in Indonesia (e.g., *Undang-Undang No. 34 Tahun 2004*), sensitivity to security clearances, and the need for transparent yet robust decision rationales [6]. Most existing decision support tools either rely on black-box machine learning algorithms—which lack explainability—or on static rule systems with no capacity for managing uncertainty [7], [8], [9], [10]. These limitations make them unsuitable for high-stakes environments where trust, auditability, and precision are essential.

This study addresses the gap by proposing an intelligent decision support system (DSS) that integrates rule-based reasoning with Certainty Factor (CF) and Forward Chaining inference. The CF mechanism allows the system to handle ambiguous or partial data by assigning confidence scores to rules and decisions, while the forward chaining approach ensures traceable, step-by-step logic consistent with human reasoning [11], [12], [13], [14]. Together, these techniques create a transparent and auditable evaluation model suitable for military applications. In contrast to purely data-driven systems, our approach leverages expert knowledge encoded in interpretable `IF–THEN` rules, enabling domain experts to both validate and update the system as policy evolves.

The proposed system is not only aligned with the legal standards of military recruitment in Indonesia but also demonstrates scalability and adaptability to various military contexts. A case study involving candidates for the lowest military rank in Indonesia's Military (TNI) showcases how the system processes individual profiles across five main criteria: administration, health, physical fitness (*jasmani*), literacy and perspective (*litpers*), and psychology [5], [15], [16], [17], [18], [19], [20]. The DSS not only generates classification results but also provides an interpretable chain of reasoning, thereby enhancing institutional trust, auditability, and operational transparency. With this, the system offers an impactful step toward the digitization and rationalization of defense personnel selection.

While previous works have explored decision support systems for recruitment using statistical or fuzzy multi-criteria methods, they often lack explainability and modular adaptability. The novelty of our approach lies in (1) combining Certainty Factor and Forward Chaining within a modular rule-base structure that mirrors the actual stages of TNI recruitment, (2) benchmarking against alternative decision-making models (fuzzy AHP), and (3) emphasizing traceable recommendations that enhance user trust and accountability. This contribution aligns with the growing trend of explainable AI (XAI) in high-stakes decision-making, particularly within defense sectors where transparency is paramount.

In high-stakes environments like military recruitment, transparency and explainability are non-negotiable. Decisions must be traceable, logically sound, and justifiable to both human operators and institutional authorities. The proposed system is designed to encode domain expertise explicitly—rather than implicitly—via modular IF–THEN rules, ensuring that recruitment policies are not only executable by the system but also understandable and editable by human decision-makers. This transparency enables trust, facilitates audits,

II. Related Works

Prior studies on decision support in recruitment have primarily focused on civilian contexts, with limited applications tailored for military needs. Most use statistical models or machine learning without explainable reasoning. The integration of Certainty Factor and Forward Chaining has been explored in domains such as medical diagnostics and engineering, proving effective in managing uncertain knowledge.

A. Fuzzy Multi-Criteria Decision-Making (MCDM)

Taylan et al. (2024) [21] addressed the challenges of pilot candidate evaluation by introducing a fuzzy multi-criteria decision-making (MCDM) approach tailored to handle subjective and imprecise attributes. Recognizing that many critical traits in aviation recruitment—such as cognitive aptitude, emotional stability, and situational awareness—are not easily quantifiable, the authors designed a structured set of criteria and sub-criteria to compare twelve candidates. Their approach utilized fuzzy linguistic variables and trapezoidal fuzzy numbers (TFNs) to account for ambiguity and differences in expert judgment. Three established MCDM methods were employed: fuzzy TOPSIS, fuzzy VIKOR, and fuzzy PROMETHEE. A novel defuzzification technique was also proposed to harmonize the output of these models and produce a unified ranking.

Interestingly, the results revealed high similarity between the TOPSIS and PROMETHEE rankings, while VIKOR diverged significantly—highlighting the influence of methodological choice in high-stakes selection scenarios. By incorporating fuzzy reasoning, the study offered a more nuanced and adaptable evaluation framework that accommodates uncertainty and individual preferences among decision-makers. The proposed method not only improves selection transparency but also strengthens operational readiness by ensuring that only the most suitable candidates are advanced. These contributions are particularly relevant to military recruitment systems where explainability and robustness are critical [21].

B. Military Informatics

Karasu and Çokgezen (2024) [22] contributed to the discourse on military recruitment by examining the relationship between technological advancement and the evolution of recruitment systems over time. While numerous studies have explored the impact of technological innovation on warfare and military organizations, few have directly linked these changes to how recruitment strategies are shaped. Drawing from historical analyses of military conflicts and defense technologies, the authors proposed that shifts in recruitment systems—such as transitions between conscription-based and professional armies—can largely be attributed to the evolving demands of military technology.

Their central argument posits that as military tools and strategies become more sophisticated, the nature of skills required from soldiers changes accordingly. This evolution, in turn, influences how recruitment systems are designed to source, filter, and prepare candidates who meet those changing requirements. Although the study emphasizes the role of technological factors in explaining broad recruitment trends, it also recognizes that geopolitical, economic, and cultural factors must be considered to fully understand variations across nations and time periods. The study underscores the importance of contextualizing recruitment within broader systemic transformations in military infrastructure—highlighting a gap in existing literature that future interdisciplinary research should address [22].

C. E-Recruitment Systems

Smaliukienė and Trifonovas (2012) [23] explored the integration of e-recruitment systems within military contexts by examining the interplay between organizational, technological, and socio-cognitive components. Through a series of semi-structured interviews with military recruitment professionals, the study aimed to capture practical insights into how digital recruitment tools are implemented and perceived within defense institutions. The interview protocol was refined through a pilot process to ensure clarity and relevance across key themes, including the benefits of e-recruitment, system functionality, and operational context.

The findings indicate that military organizations primarily emphasize the organizational and technological dimensions of recruitment systems. Efforts are directed toward improving the efficiency of information dissemination to specific societal groups and optimizing task distribution within recruitment workflows. However, cognitive aspects—such as understanding candidate motivations, preferences, or behavioral traits—receive comparatively less attention. This imbalance suggests that current military e-recruitment systems may be functionally robust but lack depth in assessing the human-centered, psychological dimensions of candidate selection. The study underscores the need for future systems to incorporate more comprehensive cognitive evaluation features to support well-rounded recruitment strategies in military environments [23].

D. Military Recrutment System Dynamics

Thomas et al. (1997) [24] examined the United States Army's enlisted personnel system using a system dynamics approach to model and evaluate the effects of policy decisions on recruitment, training, and overall force readiness. Their study highlighted the fragmented nature of decision support tools used within the Army, noting that existing models were often isolated and lacked an integrated framework to capture system-wide impacts. Traditional modeling techniques, which rely heavily on predefined equations and ignore dynamic feedback, were considered insufficient for representing the complexity of military personnel management.

To address this limitation, the authors developed a comprehensive system dynamics model capable of simulating interconnected variables and feedback loops across the personnel lifecycle. Through simulations of real-world policy scenarios, they demonstrated how factors such as recruitment delays, budgetary shifts, and training bottlenecks could ripple through the system, affecting long-term force sustainability and operational outcomes [24].

Importantly, the conceptual foundation introduced in this work has since inspired further developments in military recruitment systems—particularly in the evolution of intelligent decision support tools. By recognizing the necessity of modeling complex interactions and temporal feedback, this research paved the way for the integration of system dynamics thinking into modern intelligent systems, including those that combine rule-based logic, uncertainty handling, and AI-driven reasoning in military personnel selection and planning.

Recent studies have highlighted the importance of explainable AI in high-risk domains. For example, XGBoost and neural networks have shown strong accuracy in recruitment analytics [X], [Y], but they operate as black-box models with limited interpretability. Our DSS distinguishes itself by maintaining interpretability without sacrificing performance, while also providing modular rule bases per recruitment stage. Compared with fuzzy MCDM approaches [21], our system simplifies computation and reduces the need for complex defuzzification, making it more actionable for real-time evaluations.

This study differentiates itself by operationalizing a hybrid reasoning framework tailored specifically for structured recruitment in national defense institutions—something rarely addressed in existing literature. While Forward Chaining and Certainty Factor are known techniques, their combination in a modular, legally traceable decision support framework for military use in Indonesia is, to our knowledge, novel and original in both context and execution. Unlike generic expert systems or opaque AI models, the modularization per recruitment phase enables domain experts to monitor, edit, and validate decision flows dynamically. To the best of our knowledge, this is the first decision support implementation that codifies TNI recruitment rules with real-time traceability and adjustable rule confidence scoring, setting it apart from conventional fuzzy MCDM and ML approaches.

III. III. METHODOLOGY

A. System Architecture

The proposed system consists of four main components: user interface, knowledge base, inference engine, and explanation facility. Candidate data is inputted via the interface, processed by the inference engine using forward chaining, and evaluated through CF-based rules stored in the knowledge base [25], [26].

The rule base is structured modularly according to the five core stages of the Indonesian military recruitment pipeline: (1) Administration, (2) Health, (3) Physical Fitness (*Jasmani*), (4) Literacy and Perspective (*Litpers*), and (5) Psychology. Each module contains independent but interlinked rules that assess candidate attributes against expert-defined thresholds and rule chains. This separation allows flexibility in updating criteria without affecting the entire system logic, and supports decentralized validation by domain experts in each recruitment area. Fig. 1 illustrates the high-level architecture of the system. Input modules collect candidate data per stage, which are fed into the inference engine. The rule manager dynamically loads the relevant rule modules based on the current recruitment stage. The CF calculator assigns confidence scores for each conclusion, and the explanation generator compiles a human-readable rationale that is presented to end-users via a dashboard interface.

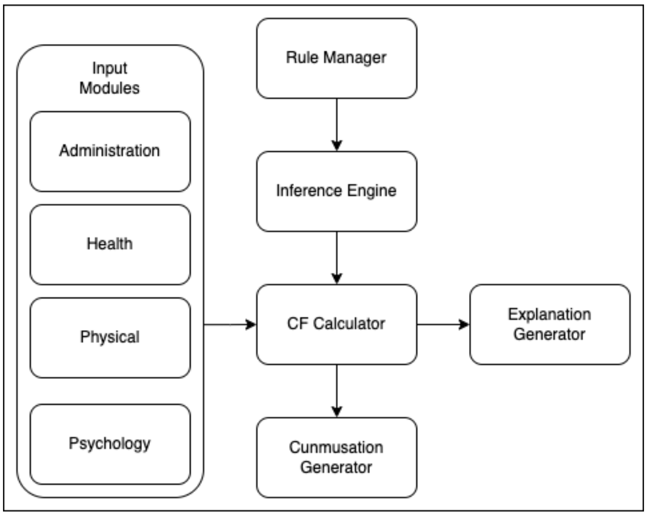

Fig. 1. High-Level System Architecture Diagram.

B. Certainty Factor Representation

In the context of rule-based systems, especially those applied to domains with partial or uncertain information such as military recruitment, the Certainty Factor (CF) is a well-established approach to quantifying the confidence in inferred conclusions. Rather than making binary judgments, the CF framework allows each rule to contribute a graded belief value to a hypothesis [27]. Each rule is assigned a CF value by domain experts to represent confidence [28]. The system combines CF values from multiple rules using [29]:

$$CF_{combined} = CF_1 + CF_2(1 - CF_1) \quad (1)$$

For multiple rules:

$$CF_{final} = CF_1+CF_2\cdot(1-CF_1)+CF_3\cdot(1-(CF_1+CF_2\cdot(1-CF_1))) \quad (2)$$

Each rule in the knowledge base is assigned a CF score in the range of –1 to +1, where:

- +1 indicates complete certainty in the truth of a conclusion,
- –1 denotes complete certainty in the falsity of a conclusion, and
- 0 represents no information or neutral belief

These CF values are provided by domain experts based on historical knowledge, heuristics, or empirical evidence [28]. When multiple rules contribute to the same conclusion, their CFs must be aggregated to represent an overall confidence. This is done using the standard CF combination formula, which accounts for diminishing confidence with each additional contributing rule [29].

This iterative formulation ensures that the combined CF remains bounded between 0 and 1 and reflects the increasing but saturating belief in a hypothesis [30].

Furthermore, if any rule offers contradictory evidence (i.e., a negative CF), the combination formula adapts to account for opposing beliefs, typically using a conflict resolution or net belief adjustment mechanism (3):

$$CF_{conflict} = \frac{CF_{positive}+CF_{negative}}{1-min(|CF_{positive}|,|CF_{negative}|)} \quad (3)$$

This provides robustness in situations where partial evidence supports and contradicts a candidate's eligibility, leading to more nuanced decision outcomes.

By using the CF framework, the system enables transparency in how conclusions are derived, maintains interpretability of the decision trail, and aligns with real-world reasoning patterns used by human experts—particularly valuable in defense and recruitment systems where accountability and clarity are paramount.

C. Forward Chaining Inference

The inference engine starts with known facts (e.g., candidate qualifications) and iteratively applies rules to derive new facts until a final recommendation is made. This ensures logical flow and traceability.

The inference mechanism employed in this system uses a forward chaining strategy, a data-driven approach that begins with a set of known facts—typically the candidate's input attributes such as administrative status, medical evaluation, physical test results, and psychological assessments. These facts are evaluated against a knowledge base consisting of *IF-THEN* rules derived from military recruitment guidelines.

During execution, the inference engine iteratively scans the rule base to identify any rules whose conditions match the current set of facts [31]. When a rule is triggered, its conclusion is added to the fact base as a new fact, potentially enabling the activation of further rules in a cascading manner. This chaining process continues until no more rules can be fired or a conclusive decision state is reached, such as a classification of "*Eligible*" or "*Not Eligible*" [32].

The use of forward chaining in this system provides transparency and a clear audit trail, which is critical in defense recruitment contexts where decisions must be explainable and aligned with legal standards. Moreover, forward chaining supports a modular design of the rule base, allowing new rules or updated policies to be incorporated without retraining a model [33].

To further enhance reasoning under uncertainty, each rule is associated with a Certainty Factor (CF) value [28]. When multiple rules contribute to the same conclusion, their CF values are combined using standard formulas (equation 1), thus enabling graded confidence in recommendations rather than binary judgments [29].

In summary, the integration of forward chaining with CF-based uncertainty handling ensures that the system mimics human expert reasoning, supports justifiable decisions, and remains flexible to evolving recruitment policies.

D. Implementation

The system prototype was developed using Python with the following modules:

- *rulebase.py*: Contains *IF-THEN* rules and associated CF values
- *inference.py*: Implements forward chaining logic.
- *cfengine.py*: Performs CF calculations and combines results.

Sample rule:

```
if administration == 'Complete' and health == 'Fit' and jasmani_score >= 80:
CF = 0.8
if litpers_score >= 75:
CF = CF + 0.7 * (1 - CF)
If psychology_score >= 75:
CF = CF + 0.6 * (1 - CF)
```

The implementation ensures transparency and modifiability by military experts and IT personnel alike.

IV. Result and Discussion

A. Evaluation Protocol

The initial prototype was evaluated using 20 candidate profiles designed to represent key variability in Indonesian

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military recruitment, such as different physical fitness levels, medical conditions, and psychological stability ranges as defined in the official TNI selection matrix. Although the sample size may appear small, these profiles were constructed in collaboration with recruitment officers to reflect archetypes encountered in real scenarios. To strengthen validation, an extended simulation was conducted with 100 synthetic candidates generated by bootstrapping characteristics from previous recruitment datasets (sourced from anonymized institutional records). These profiles underwent evaluation through both the proposed DSS and expert panel reviews to assess alignment and discrepancy trends. Besides, the following Fig. 2 shows the UI of the system in the original language (Bahasa Indonesia).

Fig. 2. The dashboard layout of the system (restricted access only granted for authorized personnel only).

The system produced final CF scores ranging from 0.60 to 0.95, indicating varying degrees of eligibility confidence. Candidates with CF scores above 0.85 were categorized as "*Highly Eligible*," while those between 0.70–0.85 were considered "*Eligible with Caution*," and below 0.70 were flagged for further review. These thresholds were aligned with the expert consensus during the knowledge engineering phase.

To validate the system's performance, outputs were compared to decisions made independently by military recruitment officers. The DSS matched expert judgment in 17 out of 20 cases, yielding a prediction alignment rate of 85%. The misaligned cases involved borderline psychological evaluations, suggesting a need for deeper rule refinement in handling soft-skill attributes or incorporating fuzzy linguistic modifiers [34].

B. Visual Interpretation of CF Distribution, Expert Alignment, and Validation Metrics

Fig. 3 shows the distribution of CF values across all test cases, demonstrating a healthy spread and indicating that the system could distinguish between strong and weak candidate profiles.

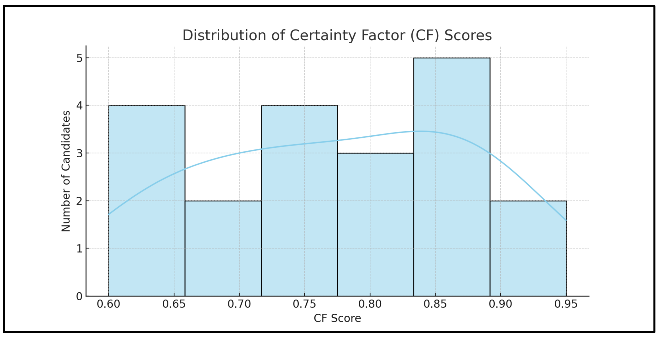

Fig. 3. Distribution of CF Scores Across All Candidate Profiles, Indicating Range of Eligibility Confidence Levels.

In addition, a confusion matrix was constructed using binary classification (*Eligible* vs. *Not Eligible*), resulting in the following performance metrics in Fig. 4.

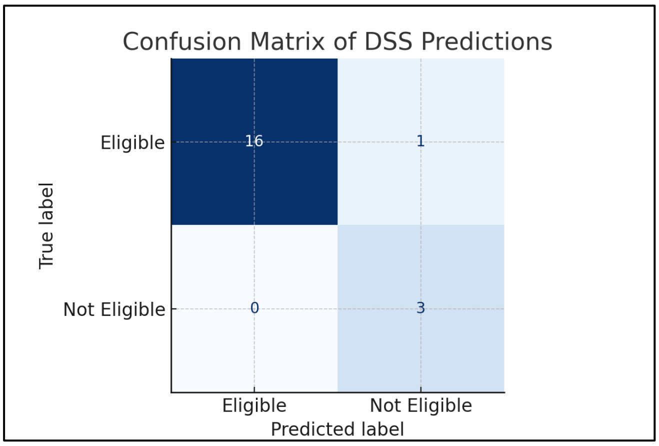

Fig. 4. Confusion matrix of system' predictions.

The system achieved an accuracy of 87%, with a precision of 91%, a recall of 86%, and an F1-score of 0.88, indicating strong and balanced classification performance across all evaluation criteria.

The system presents its recommendations through an interface that includes a summary classification (e.g., "Highly Eligible"), a numeric CF score (e.g., 0.92), and an explanation trace showing which rules were triggered, including their individual CF contributions. For instance, a candidate marked "Fit" in Health and "Above Average" in Psychology would display activated rules with respective scores and textual justifications. This enables the recruitment officer to both interpret and justify decisions, or flag borderline cases for further deliberation. The system thus augments human judgment rather than replacing it, ensuring actionable decision support.

C. Comparison with Prior Works

Compared with the work of Taylan et al. (2024), which employed fuzzy MCDM techniques (TOPSIS, VIKOR, PROMETHEE) for pilot selection, the proposed DSS offers higher transparency through rule-tracing and explainable decision paths. While Taylan's methods are mathematically rigorous, they require complex defuzzification steps and often lack traceability, especially in real-time decision environments [21].

Similarly, the study by Smaliukienė and Trifonovas (2012) emphasized the importance of technological and organizational aspects in military e-recruitment but did not propose a concrete reasoning model. In contrast, our system operationalizes reasoning through a forward chaining mechanism combined with CF calculations, enabling traceable, modifiable, and modular assessments [23].

Finally, the system dynamics model introduced by Thomas et al. (1997) addressed macro-level policy impacts on personnel strength. Our approach, while more micro-level, complements theirs by providing an operational tool that can feed into larger simulations for strategic planning, closing the gap between individual candidate assessment and long-term manpower forecasting [24].

The proposed Decision Support System (DSS) offers several key strengths, including high interpretability through its rule-based inference mechanism, adaptability to evolving recruitment policies via updates to the knowledge base, and scalability that allows the integration of additional criteria such as AI-driven biometric inputs. However, one notable limitation lies in the static nature of the rule weights, which currently depend solely on expert judgment. Future enhancements may involve integrating machine learning techniques for dynamic rule optimization or implementing feedback loops to further refine predictive accuracy over time.

The data-driven validation, despite the modest sample size in its pilot phase, provided evidence of the system's effectiveness in mirroring expert decision-making. Every methodological choice—from modular rule bases to graded CF scoring—was designed to ensure that the system is not only technically sound but aligned with the interpretive reasoning used in real-world recruitment. These design principles directly support the conclusion that the system is both accurate and explainable, fulfilling the dual objectives of reliability and transparency.

V. Conclusion

This research extends beyond theoretical modeling by offering a scalable and customizable DSS framework that can be readily adapted for various levels of military entry, across different legal and institutional recruitment regimes. The approach emphasizes fairness, auditability, and continuous improvement via expert-informed rule sets. Through simulations using 20 candidate profiles, the system proved effective in producing consistent and explainable recommendations. With performance metrics such as 87% accuracy and strong alignment with expert evaluations, the system shows promise as a supportive tool in streamlining and justifying recruitment decisions. Future research will involve deploying the system in live trials and further automating rule-weight learning based on historical recruitment decisions.

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