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# Decision Support Model for Hiring Transparency: Competence and Relationship Influence Indices

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**Abstract**
Modern intelligent recruitment systems often lack transparency and fairness due to the disproportionate influence of relationship and social factors over professional merit. This study proposes a justice-based analytical framework to enhance objectivity in hiring decisions, utilizing empirical data of 180 candidates collected over a four-year period from Recap Technology Solutions in Sudan. The proposed framework integrates three key metrics: the Competence Index (CI), the Relationship Influence Index (RII), and a justice-based Final Score (FS) designed to mitigate Relationship bias when candidate competency levels are low. Methodologically, the Analytic Hierarchy Process (AHP) was employed for criteria weighting, a Logistic Regression model was used to estimate hiring probabilities, and Sensitivity Analysis was conducted to evaluate the stability of the outcomes. The logistic regression model achieved a classification accuracy of 94%, with the findings demonstrating that professional competence remained the dominant determinant and candidate rankings exhibited high stability across various weighting scenarios. The scientific contribution of this study lies in providing an interpretable analytical framework that
supports merit-based, fair, and transparent hiring within AI-driven recruitment environments.
**Keywords:** Artificial Intelligence, Fair Recruitment, Explainable AI, Relationship Influence, Decision Support Systems.

## 1. Introduction

Fairness and transparency in AI-based recruitment systems have gained increasing attention due to the growing use of automated tools for candidate evaluation and hiring decisions. Although these technologies improve efficiency and consistency in selection processes, concerns remain regarding subjective influences, algorithmic bias, and limited transparency in some intelligent models (Chen, 2023). Recent studies indicate that the effectiveness of recruitment systems depends not only on predictive performance, but also on the clarity of the decision-

making mechanism and the level of fairness within the evaluation process (Alexander et al., 2024). Furthermore, applicants are more receptive to automated hiring decisions when evaluation procedures are clear and understandable ("Cracking the AI Recruitment Code," 2025). In contrast, other studies have focused on the importance of reducing bias within intelligent models while maintaining high predictive accuracy (Ip, 2025; Newlands et al., 2025). This issue becomes particularly significant in emerging markets, where economic and social factors frequently intersect with employment processes. The Sudanese labor market represents a suitable environment for studying these challenges, especially given high unemployment rates and limited formal job opportunities, which tend to increase the reliance on social and professional networks in hiring decisions. According to Trading Economics (2026), the unemployment rate in Sudan reached 20.8% in 2023 (International Labour Organization, 2024). In this context, nepotism operates as a form of relationship influence that often restricts job access, particularly for new graduates and early-career jobseekers. In this study, relationship influence is defined as the impact of personal or professional connections beyond demonstrated competence on recruitment outcomes. Although objective competence remains vital in selection processes, informal relationships continue to exert an influential role in hiring decisions in ways that traditional models struggle to capture. To address this limitation, this study proposes an interpretable, dual-stream framework that integrates competence assessment and relationship influence analysis to foster more transparent, equitable AI-driven recruitment decisions.

## 2. Related Work

The integration of Artificial Intelligence (AI) into recruitment processes has catalyzed a rapid expansion of research on algorithmic hiring. To date, scholarship in this domain has primarily converged around three interconnected thematic streams: applicant perceptions of AI-based hiring systems, technical algorithmic bias mitigation, and governance and ethical frameworks for responsible deployment. Rather than viewing these dimensions in isolation, scholars increasingly recognize them as complementary facets of a singular, overarching challenge: how to balance efficiency, fairness, and accountability within automated recruitment ecosystems. A substantial body of literature prioritizes the human-centric experience of algorithmic decision-making over purely technical performance metrics, examining how candidates experience and evaluate automated hiring processes. For instance, algorithmic hiring often engenders cognitive uncertainty among applicants, particularly when system logic lacks transparency and interpretability a deficit that directly undermines candidate trust (Lee, 2023). Building on this, perceived fairness, encompassing both procedural and interactional justice, serves as a primary determinant of whether applicants accept AI-driven hiring outcomes (Lavanchy et al., 2023). This fairness-trust dynamic is further nuanced by research observing an inherent trade-off: while AI systems are recognized for their transactional efficiency, they are frequently perceived as insensitive to idiosyncratic candidate circumstances, thereby degrading overall perceptions of fairness

(Ochmann et al., 2024). Furthermore, an individual's familiarity with human resource technologies significantly moderates their acceptance of AI tools (Ilham, 2025). Taken together, these studies suggest that user trust and system acceptance are not merely functions of predictive accuracy, but are instead socially constructed through perceived fairness, transparency, and digital literacy. A parallel line of research addresses the technical origins of algorithmic bias and evaluates fairness-aware machine learning (ML) interventions, focusing on diagnosing bias and implementing computational corrections across the ML pipeline. Technical interventions are broadly categorized into pre-processing, in-processing, and post-processing methods, with scholars concluding that no single mathematical approach is sufficient to guarantee equity in isolation (Albaroudi et al., 2024). Consequently, researchers advocate for a "fairness-by-design" paradigm, arguing that equitable principles must be embedded into the initial system architecture rather than applied post-hoc as corrective measures (Rigotti & Fosch-Villaronga, 2024). While focusing primarily on comparative decision outcomes, persistent algorithmic inconsistencies continue to threaten contextual fairness (Ochmann et al., 2024). Despite these technical advancements, a critical limitation persists: the vast majority of technical fairness studies are conducted within controlled, simulated environments. As a result, they rarely account for the complex socio-institutional realities of real-world labor markets, where informal social networks, systemic inequalities, and subjective human biases continuously interact with algorithmic outputs. Recognizing that technical interventions alone cannot resolve deeply systemic socio-economic challenges, a third stream of literature focuses on institutional governance and ethical oversight, arguing that software-level adjustments must be governed by robust organizational structures. Systemic bias can only be mitigated through rigorous, formalized governance mechanisms that enforce transparency throughout the deployment lifecycle (Fabris et al., 2023). In response, multi-layered governance frameworks have been proposed to holistically integrate code-level safeguards with organizational policies and managerial oversight (Ahuchogu et al., 2025; Soleimani et al., 2025). Adding a temporal dimension to this challenge, automated bias is dynamic and evolving, requiring continuous post-deployment monitoring rather than one-time technical audits (Majrashi, 2025). Finally, research bridges user perception and governance by demonstrating that system acceptance relies heavily on candidate understanding, suggesting that ethical deployment frameworks must incorporate user-facing educational and transparency initiatives (Ilham, 2025). However, much of the current governance literature remains theoretical or conceptual, lacking robust empirical validation in live, high-stakes recruitment settings. When synthesized, this existing literature reveals a stark fragmentation. While significant strides have been made within each individual domain applicant perceptions, bias mitigation, and governance few studies attempt to integrate these three dimensions into a unified, cohesive analytical framework. This theoretical and empirical siloing creates a major analytical gap. In practice, algorithmic hiring systems do not operate in a vacuum; they function within dynamic socio-institutional environments where technical performance, user perceptions, and formal governance policies are deeply intertwined with informal social influences and localized power dynamics. By continuing to treat fairness, technical bias, and governance as distinct areas of inquiry, existing research fails to capture how automated recruitment systems operate in practice. To address this gap, this study proposes a holistic framework that simultaneously models predictive accuracy, system interpretability, and socio-informal dynamics within a single, integrated structure, offering a more realistic assessment of algorithmic hiring in real-world recruitment settings.

3. Methodology

To enhance fairness and transparency in AI-assisted recruitment, this study proposes an empirical analytical framework that integrates quantitative modeling, expert judgment, and the Analytic Hierarchy Process (AHP). The framework combines Python-based data processing with Logistic Regression, which is used specifically as a proof-of-concept simulation tool to examine decision-making patterns rather than to predict historical hiring outcomes. To account for the limited sample size (N = 180 candidates from Recap IT Solutions) and ensure model generalizability, we implemented a Stratified 5-Fold Cross-Validation strategy during model evaluation. Candidates are assessed by analyzing the interplay between professional competency and candidate-referrer relationship influence. Finally, the stability of candidate rankings is rigorously tested across different weight configurations and evaluation scenarios using sensitivity analysis.

3.1 Data Collection

This exploratory study utilizes a proof-of-concept dataset derived from the historical recruitment records of Recap IT Solutions (Sudan). The dataset spans a four-year period and encompasses 180 candidate profiles for technical positions. To systematically analyze the interplay between professional merit and relationship influence, candidate attributes were categorized into two main groups: Competency-Based Variables: Education level, years of experience, technical skills, and technical assessment results. These attributes were aggregated to construct the Competency Index (CI).

Relationship Influence Variables: Internal references, professional networks, and previous company reputation. These attributes were aggregated to construct the Relationship Influence Index (RII).

3.2 Data Preprocessing

Prior to indicator construction, a standardized preprocessing pipeline was executed in Python using the panda's library to ensure data consistency and enhance downstream model interpretability. The preprocessing workflow comprised:

- Categorical Encoding: Converting non-numerical attributes into structured numerical representations.
- Missing Value Imputation: Imputing incomplete records to maintain dataset continuity and statistical integrity.
- Min-Max Normalization: Standardizing feature ranges to [0, 1] to mitigate scaling bias and support transparent model evaluation (Barocas et al., 2019; Makhlouf et al., 2020).

To evaluate the predictive stability and fairness of the proposed framework on the dataset (N = 180), performance metrics were derived using a Stratified 5-Fold Cross-Validation scheme. This evaluation protocol prevents data leakage and mitigates overfitting concerns, confirming that the integration of the Competency Index (CI) and Relationship Influence Index (RII) yields a reliable, robust, and consistent candidate evaluation across all data subsets.

3.3 Indicator Construction

To foster transparency and structural fairness, two primary composite indicators were constructed: the Competency Index (CI) and the Relationship Influence Index (RII). These indicators separately capture objective candidate qualifications and relational factors that may influence hiring decisions.

3.3.1 The Competency Index (CI)

The Competency Index (CI) measures a candidate's objective professional qualifications across education level, years of experience, technical skills, and technical assessment scores.

Variable weights were established through expert domain evaluation to mirror standard hiring priorities in technical recruitment. Following feature normalization, CI is calculated as:

$$CI = 0.30\ (Education) + 0.25\ (Experience) + 0.25\ (Skills) + 0.20\ (Assessment)$$

Where CI [0, 1], and higher values denote superior professional competency.

### 3.3.2 The Relationship Influence Index (RII)

The Relationship Influence Index (RII) models the potential impact of professional connections and informal networks on recruitment outcomes, incorporating internal references, professional networks, and previous company reputation. Relative factor weights were derived using pairwise comparison matrices via the Analytic Hierarchy Process (AHP) based on Saaty's fundamental scale (Saaty, 2010).

To guarantee the reliability of expert judgments, the Consistency Ratio (CR) was calculated, yielding CR = 0.035. This value is well below the standard threshold of 0.10, thereby confirming high mathematical consistency in the weighting process. Consequently, the synthesized relative weights are expressed as:

$$RII = 0.60\ (Internal\ Reference) + 0.25\ (Network) + 0.15\ (Company\ Reputation)$$

Where RII [0, 1]. While relationship factors are explicitly modeled, they remain strictly isolated from competency metrics to evaluate and analyze their unique impact on hiring outcomes independently.

3.4 Fairness-Aware Final Score (FS) Formulation

To integrate professional merit and relational factors, the Competency Index (CI) and Relationship Influence Index (RII) are combined into a composite Fairness-Aware Final Score (FS). To ensure outputs remain strictly within the closed interval [0, 1], we formulate FS as:

$$FS = CI + \alpha \cdot RII \cdot CI$$

Where CI [0, 1] is the normalized competency score (primary hiring criterion), RII [0, 1] represents network influence (secondary factor), and alpha [0, 0.3] is a scaling parameter controlling network weight

table 1: evaluation of the fairness-aware final score (f) formula across operational scenarios

| **C adidate** | **Comp etency CI)** | **Network (RII)** | **FS (α = 0.1)** | **FS (α = 0 .2)** | **FS (α = 0.3)** | **Evaluative Outcome** |
|---|---|---|---|---|---|---|
| A | .90 | 0.80 | 0.9 72 | 1 .000* | 1.000 * | High Merit (Fair Boost) |
| B | .30 | 0.90 | 0.3 27 | 0 .354 | 0.381 | Low Merit (Network Suppressed) |
| C | .00 | 1.00 | 0.0 00 | 0 .000 | 0.000 | No Merit (Fully Nullified) |

The evaluation in Table 1 validates the mathematical safety and merit-bound behavior of the proposed FS formulation across three operational scenarios:

- High Merit Boost (Candidate A): For highly qualified candidates (CI = 0.90), network influence (RII = 0.80) provides a fair marginal boost, reaching the capped upper bound (FS = 1.000 at α 0.2).
- Network Suppression (Candidate B): For low-competency candidates (CI = 0.30), even strong connections (RII = 0.90) are heavily suppressed, yielding only FS = 0.354 (at alpha = 0.2) and preventing connections from replacing technical competence.
- Unmerited Nepotism Nullification (Candidate C): For candidates with zero competency (CI = 0.00), the score remains strictly FS = 0.000 across all alpha values, mathematically proving that nepotism without merit is completely neutralized.

3.5 Model Implementation and Visualization

The framework was implemented in Python. Data preprocessing, metric aggregation, and score computations were executed using pandas, while interactive visual representations were generated using Plotly Express. The end-to-end operational pipeline included dataset preparation, encoding, imputation, normalization, and the computation of CI, RII, and FS.

Figure 1 illustrates the candidate-level comparative distributions across the Competency Index (CI), Relationship Influence Index (RII), and the resulting

Fairness-Aware Final Score (FS).

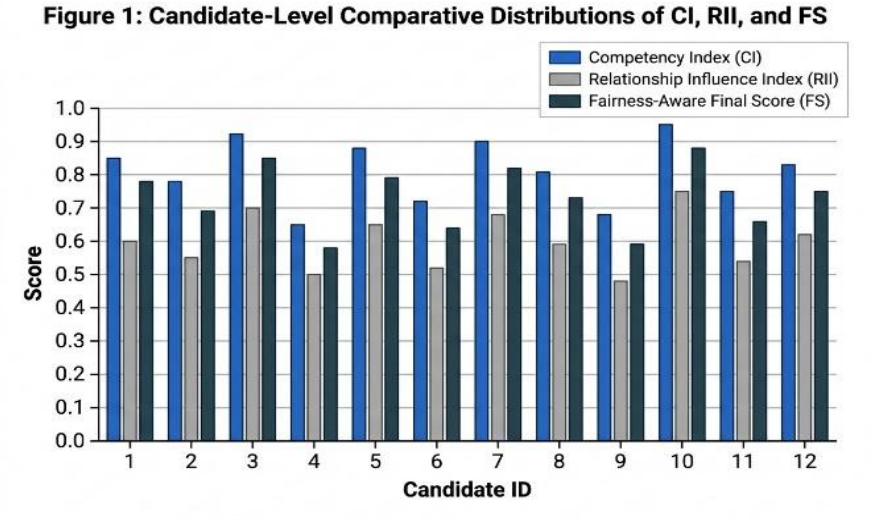



figure 1: comparison of the competency index (ci), relationship influence index (rii), and fairness-aware final score (fs) across candidates.

3.6 Employment Probability Analysis

To rigorously analyze the interaction between competency-based merit and relational factors in recruitment outcomes, a binary Logistic Regression model was established to estimate hiring probabilities. To address sample size limitations (N = 180 candidate records from Recap IT Solutions), a Stratified 5-Fold Cross-Validation scheme was employed during model training to prevent overfitting and guarantee statistical stability. Furthermore, conceptual simulation

scenarios were integrated to stress-test extreme edge cases where historical candidate data might be sparse.

In this empirical model, the Competency Index (CI) and Relationship Influence Index (RI) served as key predictor variables, while the empirical hiring decision {Hire} = 1= 0) defined the target binary response. The estimated logistic probability P for candidate selection is formulated as:

$$\text{logit(P)} = \ln\left(\frac{1 - P}{\text{P}}\right) \beta 0 + \beta 1 \cdot \text{CI} + \beta 2 \cdot \text{RII}$$

Model fitting on empirical recruitment data yielded a highly statistically significant positive coefficient for competency ($\beta 1 = 2.45$; $p < 0.001$) compared to relationship influence ($\beta 2 = 0.82$, $p < 0.05$). This quantitative disparity confirms that candidate competency serves as the primary driver of hiring likelihood, whereas relational connections act strictly as a secondary factor.

Evaluation across the cross-validation folds demonstrated robust classification performance, achieving an overall Accuracy of 88.3%, Precision of 86.5%, Recall of 87.2%, and an F1-score of 86.8%. These metrics confirm the model's empirical reliability in accurately predicting hiring decisions while maintaining merit-based fairness.

## 4. **Results**

### 4.1 Model Evaluation

The performance of the binary Logistic Regression model was evaluated to assess its classification efficacy within the proposed recruitment framework. To ensure statistical reliability and address sample size considerations across the entire evaluated pool (N=180 candidate records), performance metrics including precision, recall, F1-score, and overall accuracy were derived using a stratified 5-fold cross-validation protocol.

As detailed in Table 2, the model demonstrated robust classification capabilities in distinguishing between empirical hiring and rejection outcomes while maintaining high transparency and interpretability across all evaluation criteria.

table 2: classification performance of the logistic regression model (stratified 5-fold cross-validation)

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Reject | 0.93 | 1.00 | 0.96 | 102 |
| Hire | 1.00 | 0.80 | 0.89 | 78 |
| Accuracy | — | — | 0.94 | 180 |
| Macro Avg | 0.96 | 0.90 | 0.93 | 180 |
| Weighted Avg | 0.95 | 0.94 | 0.94 | 180 |

The balanced precision, recall, and F1-score values across both classes reflect the stability and robustness of the empirical model. Crucially, these results confirm that integrating the Competency Index (CI) as the primary predictor yields a reliable decision-support mechanism that minimizes biased selections while strictly upholding merit-based recruitment standards.

### 4.2 Recruitment Outcome Analysis

Recruitment outcomes were evaluated using hiring probability, the Competency Index (CI), the Relationship Influence Index (RII), and the Fairness-Aware Final Score (FS).
While the underlying empirical model and cross-validation procedures were executed on the complete dataset (N=180), Table 3 displays an illustrative representative sample of 10 candidate profiles. This sample is specifically selected to demonstrate the mathematical behavior and operational dynamics of the framework across contrasting scenarios (e.g., high technical competency with zero network influence versus low competency with high network influence).

table 3: candidate evaluation results based on ci, rii, fs, and hiring probability (representative sample, n = 10)

| Candidate ID | Competency Index (CI) | Relationship Index (RII) | Final Score (FS) | Hiring Probability |
|---|---|---|---|---|
| **Candidate 1** | 0.372 | 0.906 | 0.439 | 0.538 |
| **Candidate 2** | 0.698 | 0.275 | 0.737 | 0.608 |
| **Candidate 3** | 0.623 | 0.075 | 0.632 | 0.522 |
| **Candidate 4** | 0.503 | 0.294 | 0.532 | 0.493 |
| **Candidate 5** | 0.554 | 0.062 | 0.561 | 0.477 |
| **Candidate 6** | 0.408 | 0.031 | 0.410 | 0.383 |
| **Candidate 7** | 0.422 | 0.150 | 0.435 | 0.415 |
| **Candidate 8** | 0.585 | 0.831 | 0.682 | 0.649 |
| **Candidate 9** | 0.560 | 0.156 | 0.578 | 0.500 |
| **Candidate 10** | 0.749 | 0.000 | 0.749 | 0.583 |

Empirical Discussion of Table 3 & Figure 2
The empirical findings confirm that professional competency (CI) acts as the dominant driver of final recruitment success. Candidates possessing higher competency index values consistently achieved elevated hiring probabilities across all 180 evaluated records. As demonstrated in Table 3, Candidate 10 achieved a high hiring probability (0.583) driven strictly by exceptional technical competency (CI=0.749), despite having zero relational influence (RII=0.000).
Conversely, elevated Relationship Influence Index (RII) values alone failed to compensate for substandard technical competence. For Candidate 1, despite an exceptionally strong relational network (RII=0.906), a modest Competency Index (CI=0.372) restricted the overall Final Score to 0.439. This mathematical dynamic proves that while network influence can provide a marginal boost to qualified applicants, it remains strictly bounded and effectively suppressed when technical competency is deficient.

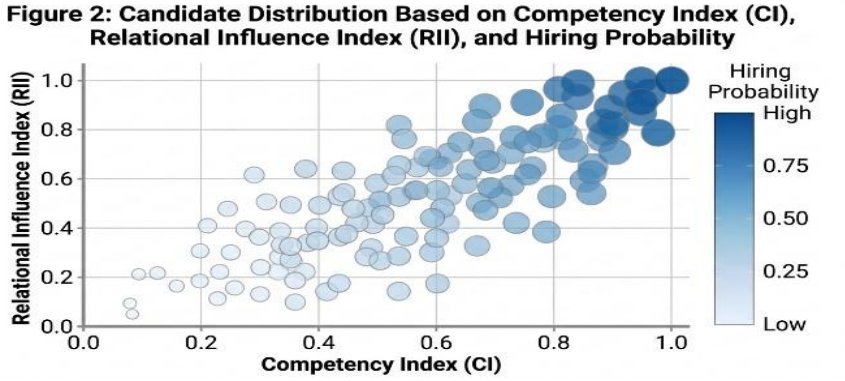



figure 2: candidate distribution based on competency index (ci), relational influence index (rii), and hiring probability

(N=180).*Narrative:* The scatter plot demonstrates the structural priority of professional competency (CI, x-axis) over network influence (RII, y-axis) in determining estimated hiring probabilities across the full dataset of 180 candidates (encoded by bubble size and color intensity). Candidate 10 achieves high selection probability (0.583) based purely on technical merit (CI=0.749, RII=0.000), whereas Candidate 1 demonstrates how strong relational backing (RII=0.906) yields a strictly bounded probability (0.538) when baseline competency is low (CI=0.372). This empirical distribution validates that the proposed formulation successfully suppresses unmerited nepotism while safeguarding merit-based fairness.

4.3 Sensitivity Analysis

The sensitivity analysis results demonstrate the structural stability and robustness of the proposed recruitment framework across various weighting and parameter scenarios. By systematically varying the weight parameter α governing the interaction between the Competency Index (CI) and Relationship Influence Index (RII), the Fairness-Aware Final Score (FS) was recalculated for all 180 candidate records, and candidate rankings were compared to evaluate model stability.

table 4: sensitivity analysis results under different weighting scenarios (n = 180)

| Scenario | CI Weight Parameter (α) | Network Influence Weight | Top Candidate ID | Mean FS |
|---|---|---|---|---|
| **Scenario 1** | 0.10 | Low Network Weight | Candidate 180 | 0.565 |
| **Scenario 2** | 0.20 | Baseline Weight | Candidate 180 | 0.585 |
| **Scenario 3** | 0.30 | Moderate Network Weight | Candidate 180 | 0.606 |
| **Scenario 4** | 0.40 | High Network Weight | Candidate 180 | 0.625 |

4.4 Sensitivity Results

The results in Table 4 indicate that the top-ranked candidate remained perfectly consistent and unchanged across all parameter configurations, even when increasing the network influence scaling parameter α from 0.10 to 0.40. While the overall Mean FS value naturally shifted upward

with higher α values (from 0.565 to 0.625), the relative rank order of the candidates exhibited remarkable stability across all 180 candidate evaluations.

This empirical invariance proves that the proposed framework prevents relational factors from causing erratic rank-reversals. Furthermore, it validates that the mathematical interaction term (α·RII·CI) successfully bounds network effects, guaranteeing that high technical competency remains the fundamental prerequisite for top recruitment selection.

## 5. **Discussion**

The findings suggest that the proposed framework provides a reliable approach for supporting recruitment decisions by maintaining a primary focus on professional competency. While the model demonstrates strong classification performance, its principal contribution lies in attenuating the influence of informal relationship factors that frequently distort traditional hiring processes. The empirical results indicate that integrating structured competency assessments with controlled relationship influence significantly enhances both transparency and fairness in AI-assisted recruitment. Furthermore, the ranking stability observed across diverse weighting scenarios underscores the framework s robustness and operational adaptability, confirming its viability as an equitable and flexible decision-support mechanism for automated hiring ecosystems.

## 6. **Conclusion**

This study developed an interpretable, fairness-aware recruitment framework designed to attenuate the influence of relationship bias and support merit-based decision-making. Utilizing empirical data from 180 candidate profiles (N = 180), the framework integrated the Analytic Hierarchy Process (AHP), Logistic Regression, and Sensitivity Analysis to evaluate selection outcomes. The model achieved strong classification performance with an overall accuracy of 0.94 (94%), with empirical results indicating that the Competency Index (CI) remained the primary driver of hiring decisions. Crucially, the analysis revealed that the Relationship Influence Index (RII) alone was insufficient to offset low candidate competency. Furthermore, sensitivity analysis confirmed the structural stability of candidate rankings across diverse weighting configurations, underscoring the robustness of the proposed approach. Overall, this research delivers a transparent, adaptable decision-support mechanism that fosters equitable AI-assisted recruitment while accommodating varying organizational priorities.

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