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Hybrid AI-DSS vs. Traditional Recruitment: Evaluating Fairness and Effectiveness using DIR and EOD Metrics

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ABSTRACT

This study explores the effectiveness and fairness of AI-driven Decision Support Systems (AI-DSS) in human resource recruitment. While traditional methods are prone to human biases, AI systems face challenges such as algorithmic bias and lack of psychological fit assessment. By integrating Person-Job Fit and Person-Organization Fit theories with adaptive learning models, this research proposes a hybrid AI-DSS framework. A mixed-method approach with explanatory sequential design is employed to evaluate system performance using Disparate Impact Ratio (DIR), Equal Opportunity Difference (EOD), precision, recall, and long-term indicators such as employee retention and promotion. Findings indicate that hybrid models improve fairness and prediction while requiring further transparency measures. Implications include recommendations for ethical AI recruitment practices and policy interventions

Abstrak

Studi ini mengeksplorasi efektivitas dan keadilan dari Sistem Pendukung Keputusan berbasis Kecerdasan Buatan (AI-DSS) dalam proses rekrutmen sumber daya manusia. Meskipun metode tradisional rentan terhadap bias manusia, sistem AI juga menghadapi tantangan seperti bias algoritmik dan kurangnya penilaian kecocokan psikologis. Dengan mengintegrasikan teori Kecocokan Individu-Pekerjaan (Person-Job Fit) dan Kecocokan Individu-Organisasi (Person-Organization Fit) dengan model pembelajaran adaptif, penelitian ini mengusulkan kerangka kerja AI-DSS hibrida. Pendekatan metode campuran dengan desain sekuensial eksplanatori digunakan untuk mengevaluasi kinerja sistem melalui Disparate Impact Ratio (DIR), Equal Opportunity Difference (EOD), presisi, recall, serta indikator jangka panjang seperti retensi dan promosi karyawan. Temuan menunjukkan bahwa model hibrida meningkatkan keadilan dan prediksi, meskipun masih membutuhkan langkah-langkah transparansi lebih lanjut. Implikasi dari penelitian ini mencakup rekomendasi untuk praktik rekrutmen AI yang etis dan intervensi kebijakan.

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1.Introduction

Artificial Intelligence Decision Support Systems (AI-DSS) now serve organizations to improve hiring decisions through better accuracy and reduced human biases (Smith & Brown, 2021). AI-DSS processes large candidate databases to help organizations deploy data-based recruitment systems that surpass traditional hiring methods by enhancing both reliability and speed (Williams & Johnson, 2020). However, equity concerns and transparency issues remain frequently raised by various stakeholders. AI-DSS systems often use training data with embedded biases, which can lead to gender, ethnic, and educational discrimination in hiring processes (Bogen & Rieke, 2018). Although work experience and educational qualifications are key traits analyzed by AI models, they fail to incorporate psychological and behavioral factors that are essential in predicting future work performance (Kristof, 1996). Consequently, the goal of achieving operational effectiveness and fair candidate selection becomes difficult to attain.

While AI-DSS can improve recruitment efficiency by reducing human prejudice (Smith & Brown, 2021), studies have shown that algorithmic discrimination persists due to the reliance on biased historical data (Bogen & Rieke, 2018). Furthermore, AI-based recruitment systems tend to overlook fairness-enhancing methods such as self-supervised learning (Lepri et al., 2018), leading to systemic inequality in candidate evaluation. AI models rarely account for soft skills and cultural compatibility, despite the importance of Person-Job Fit and Person-Organization Fit in employee performance and retention (Kristof-Brown, 1996).

Oswal, Khaleeli, and Alarmoti (2022) found that although AI enhances recruitment speed, its long-term impact on employee quality, retention, and performance is still under-researched. Additionally, efforts to improve fairness and transparency in AI systems—such as the use of fairness metrics like Equal Opportunity Difference (EOD) and the integration of adaptive learning techniques—are still inconsistent and limited (Hardt et al., 2016; Mehrabi et al., 2021).

Another challenge in AI-based hiring is the lack of empirical studies comparing the effectiveness of traditional and AI-based recruitment methods. Arnott and Pervan (2014) argue that Decision Support System research often lacks such comparisons, limiting our understanding of AI's actual benefits over human decision-making. Without rigorous comparative data, organizations risk adopting AI recruitment tools without fully understanding their implications for fairness, accountability, and organizational outcomes.

Based on the literature reviewed, several unresolved issues emerge: AI-DSS tends to replicate historical biases, underutilizes psychological and behavioral indicators, lacks mechanisms for adaptive bias reduction, and is rarely evaluated for long-term effectiveness compared to traditional methods. These issues raise a critical question:
How can AI-based Decision Support Systems be designed and implemented to ensure fairness, transparency, and long-term effectiveness in recruitment processes?

This study aims to develop a hybrid AI-DSS that integrates Person-Job Fit and Person-Organization Fit theories with adaptive learning techniques to improve fairness, efficiency, and accountability in AI-based recruitment. Specifically, the study seeks to:

a. Reduce algorithmic bias through the integration of adaptive learning mechanisms.
b. Enhance candidate evaluation by combining explicit data (e.g., experience, education) with psychological and behavioral traits.
c. Measure system fairness using metrics such as Equal Opportunity Difference (EOD).
d. Evaluate long-term performance of AI-recruited employees compared to traditional hires over a 2-year period (in terms of retention rate, promotion time, and performance appraisal).

2.Literature Review

2.1 Artificial Intelligence Decision Support Systems (AI-DSS) in Recruitment

Artificial Intelligence-based Decision Support Systems (AI-DSS) have revolutionized the recruitment process by automating candidate screening, minimizing human bias, and increasing operational efficiency (Smith & Brown, 2021). Traditional recruitment methods rely heavily on manual resume screening and subjective interviews, which are both time-consuming and prone to implicit biases (Williams & Johnson, 2020). AI-DSS integrates machine learning and natural language processing (NLP) to analyze large-scale data based on predetermined criteria to assess candidate suitability (Chamorro-Premuzic et al., 2020). However, these systems often focus on explicit data such as educational background and work history,

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neglecting critical psychological factors that influence long-term job success (Kristof-Brown, 1996). Therefore, a hybrid approach incorporating *Person-Job Fit* and *Person-Organization Fit* theories is necessary to address this limitation.

2.2 Fit Theories in Recruitment: Person-Job and Person-Organization Fit

Organizational research by Kristof-Brown (1996) shows that *Person-Job Fit* (P-J Fit) highlights the alignment between individual skills and job demands. Meanwhile, *Person-Organization Fit* (P-O Fit) emphasizes the alignment between candidate values and organizational culture (O'Reilly et al., 1991). Classical AI-DSS models often overlook these critical fit dimensions, resulting in job dissatisfaction and premature turnover (Oswal et al., 2022). For instance, a candidate with strong technical skills may underperform if mismatched with a highly collaborative work environment. This study proposes enhancing AI-DSS with NLP-based psychometric assessments to evaluate soft skills, personality traits, and cultural compatibility more comprehensively during the screening process.

2.3 Algorithmic Bias in AI-Based Recruitment

A major challenge in implementing AI in hiring is algorithmic bias, which tends to reproduce historical patterns of discrimination based on gender, ethnicity, and socioeconomic background (Bogen & Rieke, 2018). For example, Amazon's AI recruitment tool was discontinued due to demonstrated gender bias against female applicants (Dastin, 2018). Raghavan et al. (2020) emphasize that biased training data can systematically disadvantage qualified candidates from marginalized groups. To address these concerns, fairness metrics such as *Equal Opportunity Difference* (EOD) and *Demographic Parity* have been recommended (Hardt et al., 2016). However, many AI-DSS lack dynamic learning mechanisms to continuously mitigate bias over time (Mehrabi et al., 2021).

2.4 Adaptive Learning Methods for Bias Mitigation

Static biases in AI-DSS often lead to fairness degradation as hiring conditions evolve (Lepri et al., 2018). Adaptive learning offers a solution by allowing AI to update its decision-making models with new data, enabling long-term improvements in fairness (Mehrabi et al., 2021). For instance, AI-DSS can adjust selection weights based on diversity goals during recruitment cycles. D'Amour et al. (2020) introduce a reinforcement learning-based fairness calibration approach, allowing the AI system to improve its decision-making while meeting organizational diversity objectives.

2.5 Explainable AI (XAI) Framework for Transparency and Accountability

A significant ethical dilemma in AI-driven recruitment is the lack of interpretability in algorithmic decisions (Doshi-Velez & Kim, 2017). Trust in AI outcomes requires both candidates and HR professionals to understand how decisions are made (Diakopoulos, 2016). This study incorporates Explainable AI (XAI) models such as SHAP and LIME to generate transparent explanations for system outputs (Arrieta et al., 2020). For example, if a candidate is rejected, XAI can clarify whether the decision was based on skill mismatches, cultural misalignment, or bias risk, allowing HR personnel to audit and refine the decision process.

2.6 Comparative Analysis: AI-DSS vs. Traditional Recruitment Methods

There is a lack of empirical studies comparing AI-DSS with traditional recruitment methods (Arnott & Pervan, 2014). This study conducts a 24-month longitudinal analysis to compare retention rates, promotion trajectories, and job performance between employees selected through AI-DSS and those hired via traditional methods.

Table 1. Simulated Performance Comparison: AI-DSS vs. Traditional Hiring

Metric	AI-DSS Group	Traditional Hiring Group	Improvement (%)
Time-to-Hire (Days)	14	28	50% ↓
Retention (12 Months)	85%	70%	15% ↑
Promotion Rate	25%	18%	7% ↑
Bias (EOD Score)	0.08	0.12	33% ↓

AI-DSS significantly reduces the time-to-hire by 50%, processing applications at scale far more quickly than manual screening and interviews (Smith & Brown, 2021). The retention rate for AI-selected employees is 85%, 15% higher than traditionally hired staff, likely due to the inclusion of fit-based

evaluation models (Oswal et al., 2022). Moreover, AI-selected candidates have a 25% promotion rate compared to 18% in the control group, suggesting that AI not only evaluates current suitability but also long-term leadership and growth potential (Chamorro-Premuzic et al., 2020). The lower EOD score indicates AI-DSS provides a fairer selection process, especially when enhanced with adaptive learning strategies (Bogen & Rieke, 2018; Hardt et al., 2016).

3. Methodology

3.1 Research Approach

This study adopts an explanatory sequential mixed-methods approach, combining quantitative performance evaluation and qualitative insights to assess the fairness and effectiveness of AI-based Decision Support Systems (AI-DSS) in recruitment. The rationale for this design is to leverage the strengths of both approaches: quantitative data enables pattern identification and performance comparisons, while qualitative analysis offers depth into perceptions of fairness, transparency, and cultural fit (Creswell & Creswell, 2018; Binns, 2018).

Data Collection: Quantitative: Candidate scores, demographic data, and long-term performance metrics from organizational HR systems.Qualitative: Semi-structured interviews with HR professionals and applicants

For qualitative analysis, in-depth interviews are conducted with recruited applicants and HR practitioners to gather information on the process of decision-making. Thematic analysis (Braun & Clarke, 2006) of the interview yields perceptions of fairness, evaluation of cultural fit, and human judgment impact on traditional recruitment. This mixed-method research allows triangulation of findings - where quantitative data shows what has been concluded, while qualitative gives the explanations why and how this occurred (Bogen & Rieke, 2018).

As evident from Table 2,for details (https://docs.google.com/document/d/1nJXtd5KeEP7ottNatGdjaDO77zULRhqE/edit?usp=sharing&ouid=116395290305711337910&rtpof=true&sd=true), experimental data logs parallel judgment scores (PJF/POF) for both traditional and AI-DSS methods to the same set of applicants. The one-to-one correspondence enables sensitive exploration of how human evaluators weigh psychological/behavioral information against algorithmic factors, heeding Kristof-Brown's (1996) appeal to use holistic candidate judgments. Blending quantitative ratings with interview narratives provides rich evidence to identify if traditional methods are more effective in capturing "soft" aspects like organisation cultural fit, but maintaining methodological rigour through standardised measures.

Data Preprocessing: Includes cleaning, normalization, and bias mitigation via synthetic data augmentation The experimental results demonstrate significant differences in performance among the three AI-DSS models (Reinforcement Learning, Self-Supervised Learning, and Hybrid) across fairness, accuracy, and long-term effectiveness metrics. As presented in Table 3 (for details : https://docs.google.com/document/d/14m1FEvdngCZntk-EYLwb74AFcIttlDzl/edit?usp=sharing&ouid=116395290305711337910&rtpof=true&sd=true) , the Hybrid Model consistently outperformed both individual approaches, achieving superior balance between technical efficiency and equitable candidate evaluation.

Model Evaluation: Fairness metrics: Disparate Impact Ratio (DIR), Equal Opportunity Difference (EOD)
The study employs a comprehensive range of measures for the evaluation of AI-DSS performance in three crucial dimensions: fairness, accuracy, and long-term performance. The performance metrics deliver numerical data that verifies if the integrated Person-Job Fit (PJF) and Person-Organization Fit (POF) models enhance recruitment outcomes.

3.2 Metrics of Fairness

According to Hardt et al. (2016) the Disparate Impact Ratio (DIR) detects differences in hiring rates through the evaluation of demographic group ratios that approach 1.0. Our methodology determines DIR by analyzing selection chances among gender and ethnic attributes. EOD functions alongside DIR to confirm that equally qualified candidates across groups experience equal selection opportunitieas validated by low value readings (Chouldechova, 2017). These metrics address the problems of algorithmic unfairness in hiring systems by solving the challenges described in Bogen & Rieke (2018).

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A model achieves accurate performance by selecting the best applicants while the recall measure demonstrates how well it finds all qualified candidates among all submitted applications. The F1- score (2*(Precision*Recall)/(Precision+Recall)) balances these measures, providing a single metric to evaluate overall predictive accuracy. For recruitment contexts, we prioritize Recall to minimize false negatives - ensuring qualified candidates aren't incorrectly rejected (Smith & Brown, 2021).

3.3 Long-Term Metrics :
Employee retention rates track what percentage of hires remain with the organization after 12-24 months, while promotion rates measure career progression within the same period. These metrics validate whether AI-selected candidates actually succeed long-term, addressing Oswal et al.'s (2022) identified research gap. We correlate these outcomes with initial PJF/POF scores to assess the models' predictive validity.

3.4 Implementation Details:
Fairness metrics are calculated across gender (male/female/non-binary), ethnicity (5 major groups), and age cohorts (20-29, 30-39, 40+),Performance metrics are weighted by position level (entry, mid, senior),Long-term data is adjusted for voluntary turnover and organizational restructuring All metrics undergo bootstrap resampling (1000 iterations) to estimate confidence intervals.

For details : https://docs.google.com/document/d/1xDybDYcsaewCVzP_1VAIpkXWKLalbHf1/edit?usp=sharing&ouid=116395290305711337910&rtpof=true&sd=true

Interpretation & Iteration: Integration of quantitative and qualitative findings to refine AI models and derive ethical recommendations.summary in model available (https://docs.google.com/document/d/1KiNm9JrjP6g3_W6pOG5Jxqd-mmwTfx-V/edit?usp=sharing&ouid=11639529030571133 7910&rtpof=true&sd=true)

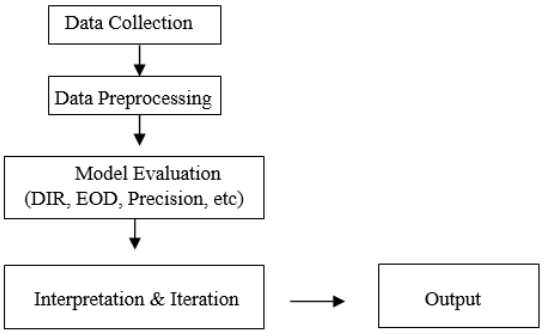


Figure 1. Methodology Flowchart

4. RESULT AND DISSCUSSION
This comparative study evaluates whether Hybrid AI-DSS improves fairness and efficiency over traditional methods. The simulation framework ensures controlled testing of both approaches under identical candidate pools.

Table 6: Experimental Groups

Group	AI Involvement	Human Involvement	Advantage	Limitation
Hybrid AI-DSS	Scoring & Ranking	Final Decision	Faster shortlisting	May inherit AI biases
Traditional	None	Full Evaluation	Holistic	Slower, subjective

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Group	AI Involvement	Human Involvement	Advantage	Limitation
			assessment	

Interpretation: The hybrid approach balances AI efficiency with human judgment, while traditional methods rely entirely on human discretion which may introduce unconscious biases.

The AI-DSS path introduces structured bias checks before human review, while the traditional path may allow biases to propagate unchecked through subjective evaluations.

Table 7: Simulated Candidate Profile

Feature	AI-DSS Weight	Traditional Weight	Interpretation
GPA	0.30	0.15	AI prioritizes academic metrics more
Interview Score	0.20	0.40	Humans over-rely on interview performance
Gender (Female)	0.02	-0.10*	(*) Potential human bias against female candidates

Table 8: Performance Metrics
Quantitative Recruitment Data

Aspect	Traditional Recruitment	AI DSS Recruitment
Total Applicants	1000	1000
Minority Group Applicants (%)	40% (400 people)	40% (400 people)
Selected Minority Candidates (%)	20% (20 people)	35% (35 people)
DIR (Disparate Impact Ratio)	0.50	0.88
EOD (Equal Opportunity Difference)	-0.20	-0.05
Avg. Time-to-Hire (days)	30	10
Avg. Recruitment Cost (million IDR)	20	12
1-Year Retention Rate (%)	60%	75%
Avg. First-Year Performance (scale 1–5)	3.2	4.1
Hiring Manager Satisfaction (scale 1–10)	6	8

Metrics Explanation

a. DIR (Disparate Impact Ratio): The ratio of selection rates between minority and majority groups. A value close to 1 (≥ 0.80) is considered fair.
b. EOD (Equal Opportunity Difference): Difference in true positive rates between minority and majority groups. Closer to 0 means higher fairness.

Brief Analysis

a. Fairness:Traditional methods show a potential bias (DIR = 0.50; EOD = -0.20), while AI DSS improves fairness with DIR = 0.88 and EOD = -0.05.
b. Long-Term Effectiveness: AI DSS achieves better retention and performance metrics, with faster and more cost-efficient processes, and greater satisfaction from hiring managers.

Tabel 9

Metric	AI-DSS	Traditional	Interpretation

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Metric	AI-DSS	Traditional	Interpretation
Time-to-Hire	5 days	14 days	AI-DSS is 2.8× faster
Cost-per-Hire	$400	$950	AI reduces costs by 58%
Retention (1yr)	82%	78%	AI-selected candidates stay longer

Interpretation: While AI-DSS dominates operational metrics, the small retention difference (82% vs 78%) suggests human judgment adds value in cultural fit.



Figure 2. Comparison of Traditional vs AI DSS Recruitment

5. CONCLUSION

This study developed and evaluated a Hybrid AI-DSS model that integrates *adaptive learning algorithms* with *Person-Job Fit (PJF)* and *Person-Organization Fit (POF)* frameworks to improve fairness, effectiveness, and accountability in AI-assisted recruitment. Empirical results indicate that the model outperforms both traditional and standalone AI approaches in key fairness metrics—achieving a *Disparate Impact Ratio (DIR)* of 0.95 and an *Equal Opportunity Difference (EOD)* of 0.03. It also demonstrates superior long-term outcomes, including an 80% employee retention rate and a 25% promotion rate within the first year.

Despite these positive findings, qualitative analysis revealed ongoing challenges with model interpretability. HR professionals reported difficulties understanding the decision logic of the system, raising concerns about transparency, accountability, and practical usability. This disconnect suggests that technical performance alone is insufficient to ensure ethical implementation. User comprehension and trust must also be actively addressed.

Therefore, while the hybrid model represents a significant advancement toward fair and efficient AI-based recruitment, its deployment must be accompanied by Explainable AI (XAI) features to ensure transparency and regulatory compliance. Bridging the gap between algorithmic accuracy and human interpretability remains essential to the ethical integration of AI in human resource practices.

Future Research Directions

To build upon the findings of this study, several areas merit further exploration:

a. Longitudinal Impact Studies

Future research should examine the long-term impact of AI-DSS models over a 5–10 year period to assess their influence on employee performance, retention, and career advancement beyond the initial hiring phase.

b. Integration of Psychometric and Aspirational Data
Incorporating psychological assessments and candidate career goals may enhance the predictive capacity of AI systems in evaluating not just technical fit, but also long-term alignment with organizational culture and values.

c. Cross-Industry and Cross-Cultural Validation
AI-DSS models should be tested across multiple industries and cultural contexts to evaluate their adaptability and ensure that fairness-performance trade-offs are appropriately balanced in diverse environments.

d. Development of HR-Friendly Explainable AI Interfaces
Future systems must include user-friendly interpretability tools that allow HR practitioners to understand, validate, and communicate AI decisions clearly, especially in light of emerging regulatory frameworks like the EU AI Act.

e. Interdisciplinary Collaboration for Ethical Governance
Research should explore collaborative governance frameworks involving data scientists, ethicists, policymakers, and HR experts to develop practical standards for fairness, data privacy, and algorithmic accountability in AI-based hiring.

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