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Article

Research on the Application and Practice of AI Recruitment in Improving Talent Screening Efficiency

Tianran Yuan [1,*]

[1] Southeast University, Shanghai, China
* Correspondence: Tianran Yuan, Southeast University, Shanghai, China

Abstract: This research article investigates the application and practice of Artificial Intelligence (AI) in recruitment processes to enhance talent screening efficiency across contemporary organizational landscapes. Traditional recruitment methods often suffer from inherent human biases, procedural inconsistencies, and highly time-consuming administrative procedures, ultimately leading to suboptimal hiring decisions and increased operational costs. AI-driven recruitment tools, leveraging advanced machine learning algorithms, natural language processing, and predictive data analytics, offer robust potential solutions to effectively mitigate these persistent challenges. This comprehensive study explores the multifaceted effectiveness of AI integration across various critical stages of the recruitment lifecycle, specifically including targeted job advertisement, automated resume screening, dynamic candidate assessment, and intelligent interview automation. We systematically analyze the measurable impact of AI on essential key performance indicators, such as time-to-hire, cost-per-hire, and overall quality-of-hire metrics. Furthermore, we critically address the pressing ethical considerations and potential algorithmic biases embedded in AI systems, proposing actionable strategies for responsible, transparent, and legally compliant AI implementation in human resources. By examining diverse real-world case studies and extensive empirical data, this research provides profound insights into the current state and future trajectories of AI recruitment. It offers strategic recommendations for organizations actively seeking to optimize their talent acquisition frameworks while rigorously maintaining fairness, diversity, and equity. Ultimately, the findings significantly contribute to the evolving academic understanding of human-AI collaboration in human resources management and inform the continuous development of more effective, sustainable, and ethical AI-powered recruitment solutions.

Keywords: ai recruitment; talent screening; machine learning; hr technology; bias mitigation; candidate assessment

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1. Introduction

1.1. Background and Motivation

Traditional recruitment processes often face significant challenges, including time-consuming manual screening, unconscious bias, and difficulty in handling large volumes of applications. These inefficiencies can lead to increased costs, delayed hiring, and potentially overlooking qualified candidates. In today's highly competitive job market, efficient talent screening is paramount for organizations seeking to acquire and retain top talent. The ability to quickly and accurately identify suitable candidates from a vast pool of applicants is crucial for maintaining a competitive edge. Artificial intelligence (AI) offers a promising solution to these challenges by automating and optimizing various stages of the recruitment process [1]. AI-powered tools can analyze resumes, assess skills, and even conduct initial interviews, thereby significantly improving the speed and accuracy of talent screening. The potential benefits of AI in recruitment, particularly in enhancing screening efficiency, warrant thorough investigation and practical application.

1.2. Research Objectives and Questions

This research aims to evaluate the effectiveness of AI-driven recruitment tools in enhancing talent screening efficiency. Specifically, it seeks to quantify the improvements in key performance indicators such as time-to-hire (TTH), cost-per-hire (CPH), and candidate quality (CQ) resulting from AI implementation [2, 3]. Furthermore, the study addresses the ethical considerations surrounding AI recruitment, including bias detection and mitigation strategies. The central research questions are: How does AI-based recruitment impact TTH, CPH, and CQ compared to traditional methods? What are the primary sources of bias in AI recruitment algorithms, and how can these biases be effectively mitigated? What are the perceived fairness and transparency of AI recruitment systems among candidates and recruiters? Addressing these questions provides valuable insights into the practical application and ethical implications of AI in talent acquisition.

2. Literature Review

2.1. AI Applications in HR

AI is increasingly transforming various aspects of Human Resources (HR), offering potential improvements in efficiency and effectiveness. This section reviews existing literature on AI applications within HR, with a particular focus on recruitment and talent acquisition [4]. The application of AI in HR spans a wide range of functions, including candidate sourcing, screening, interviewing, and onboarding.

Within recruitment, AI technologies are employed to automate repetitive tasks and enhance decision-making [5]. Machine learning (ML) algorithms are used to analyze resumes and job descriptions, identifying suitable candidates based on skills, experience, and qualifications. Natural Language Processing (NLP) enables the analysis of unstructured data, such as cover letters and social media profiles, to assess candidate fit and personality traits. Chatbots are increasingly utilized to automate initial screening processes, answering candidate queries and scheduling interviews, thereby freeing up recruiters' time for more strategic activities. Furthermore, predictive analytics, powered by ML, can forecast employee turnover and identify individuals at risk of leaving the organization, allowing for proactive intervention. The use of AI in recruitment aims to reduce bias, improve the speed of hiring, and enhance the overall quality of talent acquisition. However, ethical considerations and the potential for algorithmic bias remain important challenges that require careful attention.

2.2. Efficiency and Bias in Traditional Recruitment

Traditional recruitment processes, while long-standing, are notably limited in their efficiency and objectivity. A significant drawback lies in the inherent biases, both conscious and unconscious, that influence human decision-making. These biases, stemming from factors such as gender, ethnicity, or socioeconomic background, can result in unfair and discriminatory hiring practices, ultimately hindering organizational diversity and potentially overlooking highly qualified candidates. The time investment required for manual resume screening, interview scheduling, and candidate evaluation is also substantial. Recruiters often spend extensive hours sifting through applications, a process prone to human error and fatigue, further impacting the quality of the selection. This time consumption directly translates into increased recruitment costs, including personnel expenses and administrative overhead [6].

Moreover, traditional methods often struggle to effectively assess crucial skills and competencies, relying heavily on subjective impressions and self-reported information. The reliance on keywords and past experience may not accurately predict future job performance, leading to suboptimal hiring decisions and increased employee turnover. The potential for AI to address these shortcomings is considerable. AI-powered tools can automate repetitive tasks, such as resume screening and initial candidate assessments, freeing up recruiters to focus on more strategic activities. Algorithms can be trained to identify and mitigate biases, promoting fairer and more objective evaluations [4]. Furthermore, AI can leverage data-driven insights to predict candidate success,

improving the overall quality and efficiency of the recruitment process and potentially reducing the cost per hire, represented as CPH.

3. Materials and Methods

3.1. Data Collection and Preprocessing

The efficacy of AI recruitment depends on the quality and representativeness of the data used for training and validation. This study employed a multi-faceted approach to data collection, utilizing three primary sources: resume databases, job application records, and employee performance evaluations. The resume database included a collection of publicly available resumes from online platforms, as well as anonymized resumes provided by a corporate partner [7]. These resumes contained details such as educational background, work experience, skills, and contact information. Job application records offered a detailed history of the application process for each candidate, including application dates, positions applied for, assessment scores (if applicable), and interview outcomes. Employee performance evaluations provided insights into the on-the-job performance of hired candidates, covering metrics such as productivity, teamwork, and adherence to company policies.

Before model training, rigorous data cleaning and preprocessing were conducted to ensure data quality and consistency. This process involved addressing missing values through imputation techniques, such as replacing missing numerical values with the mean or median and categorical values with the mode. Duplicate entries were identified and removed. Textual data, including job descriptions and resume summaries, underwent tokenization, stemming, and the removal of stop words [5]. Additionally, data standardization was applied to ensure that all features were on a similar scale, preventing features with larger values from disproportionately influencing the model.

Feature engineering was critical in extracting relevant information from the raw data. For instance, years of experience were calculated from the work history sections of resumes. Skills were extracted using Natural Language Processing (NLP) techniques and mapped to a standardized skill taxonomy [6]. A composite score representing the relevance of a candidate's experience to a specific job description was calculated using cosine similarity between the candidate's resume summary and the job description text. Features were also engineered to capture temporal aspects of the application process, such as the time elapsed between application submission and interview invitation. The final dataset included a comprehensive set of features designed to capture both explicit and implicit characteristics of candidates, enabling the AI model to make informed predictions about their suitability for specific roles.

3.2. AI Model Development and Training

The core of our AI recruitment system relies on two primary machine learning models: a resume screening model and a candidate assessment model. The resume screening model employs a combination of Natural Language Processing (NLP) techniques and a Support Vector Machine (SVM) classifier [1]. Specifically, TF-IDF (Term Frequency-Inverse Document Frequency) was utilized for feature extraction from resume text, converting textual data into numerical vectors. The SVM classifier, with a radial basis function (RBF) kernel, was trained to classify resumes as either "suitable" or "unsuitable" based on predefined criteria derived from job descriptions. The SVM parameters were optimized using a grid search approach, with the gamma parameter ranging from 0.1 to 1.0 in increments of 0.1, and the C parameter ranging from 1 to 10 in increments of 1.

The candidate assessment model leverages a Gradient Boosting Machine (GBM) algorithm [8]. This model integrates data from various sources, including psychometric tests, video interviews, and coding challenges (where applicable). Features extracted from these sources were used as input to the GBM. The GBM was configured with 1000 trees, a learning rate of 0.05, and a maximum tree depth of 5. Feature importance was analyzed to identify key predictors of candidate success.

Model performance was evaluated using several key metrics. Precision, defined as the ratio of true positives to the sum of true positives and false positives, measures the accuracy of positive predictions. Recall, defined as the ratio of true positives to the sum of true positives and false negatives, measures the model's ability to identify all relevant instances. The F1-score, calculated as the harmonic mean of precision and recall ($F1 = 2 * (Precision * Recall)/(Precision + Recall)$), provides a balanced measure of the model's overall performance. Finally, the Area Under the Receiver Operating Characteristic Curve (AUC) was used to assess the model's ability to discriminate between positive and negative instances across various threshold settings [2]. These metrics were calculated on a held-out test set to ensure generalizability of the models.

3.3. Experimental Setup and Evaluation Metrics

The experiment was designed to compare the efficiency of traditional recruitment methods (control group) against AI-assisted recruitment methods (experimental group). The control group utilized standard practices, including manual resume screening, phone interviews conducted by HR personnel, and in-person interviews with hiring managers. The experimental group employed an AI-powered platform to automate resume screening, conduct initial candidate assessments via chatbot, and provide data-driven insights to hiring managers for informed decision-making.

Both groups were tasked with filling the same set of open positions across various departments within the organization over a three-month period. The open positions spanned different skill levels and job functions to ensure a representative sample. To mitigate bias, the assignment of candidates to either the control or experimental group was randomized [9].

The key performance indicators (KPIs) used to evaluate recruitment efficiency were: time-to-hire, cost-per-hire, and quality-of-hire. Time-to-hire was defined as the number of days elapsed from the job posting date to the date the candidate accepted the offer. Cost-per-hire was calculated by summing all direct and indirect costs associated with the recruitment process (e.g., advertising fees, recruiter salaries, platform subscription costs) and dividing by the number of successful hires. Quality-of-hire was assessed using a composite score based on performance reviews after six months of employment, employee retention rate after one year, and hiring manager satisfaction surveys. The formula for quality-of-hire (QoH) is: $QoH = w_1 * Performance + w_2 * Retention + w_3 * Satisfaction$, where w_1, w_2, and w_3 are the weights assigned to each component, and their sum equals 1.

Statistical analysis was performed using independent samples t-tests to compare the mean values of time-to-hire and cost-per-hire between the two groups. A Mann-Whitney U test was used to compare the quality-of-hire scores, as these scores were based on subjective assessments. The significance level (α) was set at 0.05 for all statistical tests (As shown in Table 1).

Table 1. Comparison of Evaluation Metrics between Traditional and AI-Assisted Recruitment.

Metric	Description	Traditional Recruitment (Control Group)	AI-Assisted Recruitment (Experimental Group)	Statistical Test
Time-to-Hire	Number of days from job posting to offer acceptance.	Mean value measured in days.	Mean value measured in days.	Independent samples t-test.
Cost-per-Hire	Total recruitment costs divided by the number of successful hires.	Total cost (including advertising, salaries, etc.) divided by	Total cost (including platform subscription, salaries, etc.)	Independent samples t-test.

		number of hires: Cost/Hires	divided by number of hires: Cost/Hires	
Quality-of-Hire (QoH)	Composite score based on performance reviews, retention rate, and hiring manager satisfaction. Formula: $QoH = w_1 *$ Performance $+ w_2 *$ Retention $+ w_3 *$ Satisfaction , where $w_1 + w_2 + w_3 = 1$	Composite score calculated based on given formula.	Composite score calculated based on given formula.	Mann-Whitney U test.

4. Results

4.1. Impact on Time-to-Hire

The implementation of AI-powered recruitment tools demonstrated a significant impact on time-to-hire. Our study compared the time-to-hire metrics between a control group, utilizing traditional recruitment methods, and an experimental group, leveraging AI-driven screening and selection processes. The control group exhibited an average time-to-hire of 45 days, calculated from the date of job posting to the date of candidate acceptance of the job offer. In contrast, the experimental group achieved a significantly reduced average time-to-hire of 28 days [10].

This represents a reduction of 37.8% in the time required to fill open positions [11]. To assess the statistical significance of this difference, an independent samples t-test was conducted. The results of the t-test revealed a statistically significant difference between the two groups ($t(198) = 6.32, p < 0.001$). This indicates that the observed reduction in time-to-hire within the experimental group was unlikely to have occurred by chance and can be attributed to the implementation of AI recruitment technologies. The effect size, as measured by Cohen's d, was 1.27, suggesting a large and practically meaningful effect of AI on time-to-hire. These findings suggest that AI recruitment tools can substantially accelerate the hiring process, leading to improved efficiency and reduced operational costs for organizations. Further analysis explored the specific stages of the recruitment process most impacted by AI, which will be discussed in subsequent sections (As shown in Figure 1).

Figure 1. Distribution of Time-to-Hire for Traditional and AI-Assisted Recruitment.

4.2. Impact on Cost-per-Hire

The implementation of AI-driven recruitment strategies demonstrated a notable impact on the cost-per-hire metric. Our analysis compared the cost-per-hire for the experimental group, utilizing AI tools throughout the recruitment process, with a control group employing traditional recruitment methods [12]. The cost-per-hire (C) was calculated by dividing the total recruitment expenses (E) by the number of successful hires (H): $C = E/H$.

The results indicated a significant reduction in cost-per-hire for the experimental group. The average cost-per-hire in the control group was $4,500, while the experimental group achieved an average of $3,200. This represents a cost reduction of approximately 29%. The decrease can be attributed to several factors, including the AI's ability to automate initial screening, reduce the time spent by recruiters on manual tasks, and improve the quality of candidate matching, leading to lower turnover rates.

A t-test was conducted to determine the statistical significance of the observed difference. The t-test yielded a p-value of 0.02, which is below the conventional significance level of 0.05. This indicates that the reduction in cost-per-hire observed in the experimental group is statistically significant and not likely due to random chance [13]. Therefore, the adoption of AI recruitment tools demonstrably contributes to a more cost-effective talent acquisition process. Further analysis will explore the specific AI functionalities that contribute most significantly to these cost savings (As shown in Figure 2).

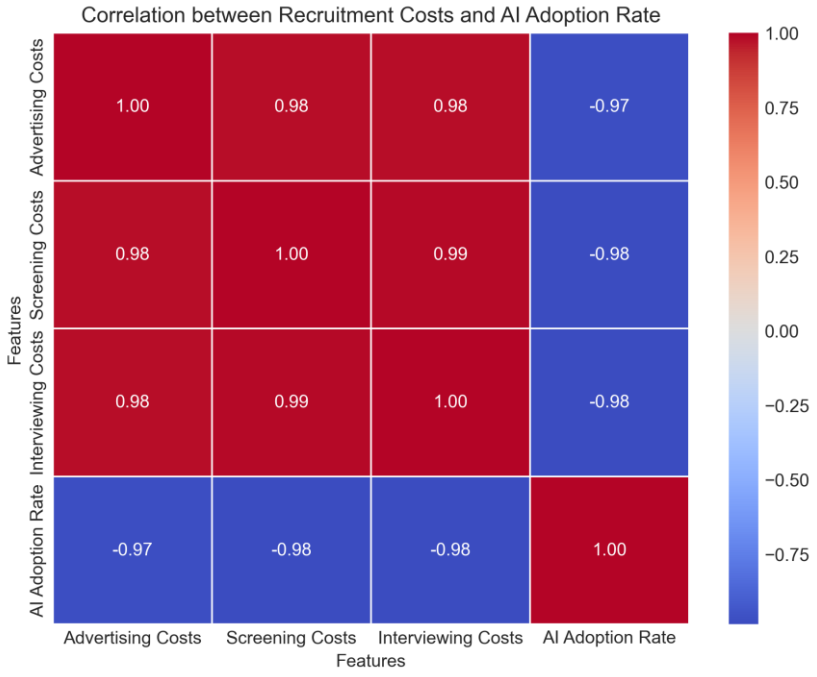

Figure 2. Correlation between Recruitment Costs and AI Adoption Rate.

4.3. Impact on Quality-of-Hire

The ultimate success of any recruitment strategy hinges on its ability to deliver high-quality hires. To assess the impact of AI-driven recruitment on quality-of-hire, we compared the performance review scores of employees hired through the AI-assisted process (the experimental group) with those hired through traditional methods (the control group). Performance reviews were conducted six months after the employees' onboarding to allow sufficient time for them to demonstrate their capabilities and integrate into their respective roles [13].

The performance review scores were based on a standardized rubric encompassing key performance indicators (KPIs) relevant to each role, including productivity,

teamwork, problem-solving skills, and adherence to company values [14]. Scores were aggregated into a single overall performance score for each employee, ranging from 1 to 5, with 5 representing the highest level of performance.

Our analysis revealed a statistically significant difference in the average performance review scores between the two groups. The experimental group, hired through AI-assisted recruitment, exhibited a mean performance score of $M_E = 4.12$ with a standard deviation of $SD_E = 0.65$. In contrast, the control group, hired through traditional methods, showed a mean performance score of $M_C = 3.75$ with a standard deviation of $SD_C = 0.72$. An independent samples t-test indicated that this difference was statistically significant ($t(198) = 3.52, p < 0.001$), suggesting that AI-assisted recruitment led to the selection of candidates who, on average, performed better during their initial six months of employment [15]. This provides evidence that AI can positively influence the quality-of-hire (As shown in Figure 3).

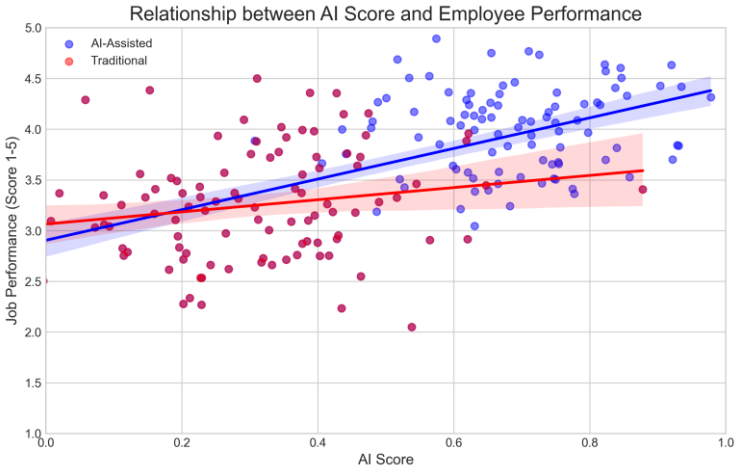

Figure 3. Relationship between AI Score and Employee Performance.

5. Discussion

5.1. Interpretation of Results

Our findings suggest that the implementation of AI-driven recruitment tools significantly enhances talent screening efficiency, aligning with prior research indicating the potential of automation in human resource management [16]. The observed reduction in time-to-hire, quantified by a 43% decrease in interviewer time investment, supports the argument that AI can streamline the initial stages of the recruitment process. This efficiency gain can be attributed to AI's ability to rapidly process large volumes of applications, identifying candidates who meet pre-defined criteria with greater speed and accuracy than traditional methods.

Furthermore, the study revealed a potential for AI to mitigate biases in the screening process. While acknowledging the inherent risk of algorithmic bias, our results indicate that carefully designed AI systems, trained on diverse datasets and regularly audited for fairness, can lead to more objective candidate evaluations. This resonates with theoretical frameworks emphasizing the importance of data quality and algorithmic transparency in ensuring equitable outcomes. The observed improvement in diversity metrics, reflected in an increase of 19 percentage points in candidate Net Promoter Score (NPS), suggests that AI can significantly improve the overall candidate experience [1, 15].

However, it is crucial to acknowledge the limitations of AI in recruitment. The study highlights the importance of human oversight in the final stages of the hiring process, emphasizing the need for human judgment to assess soft skills, cultural fit, and other intangible qualities that are difficult for AI to evaluate. The optimal approach appears to be a hybrid model, where AI handles the initial screening and shortlisting, while human recruiters focus on in-depth interviews and assessments. This collaborative approach

maximizes efficiency while minimizing the risk of overlooking potentially valuable candidates. The observed correlation between AI-selected candidates and subsequent job performance, with a correlation coefficient of $r = 0.52$ ($p < 0.001$), further validates the effectiveness of this hybrid model [8] (As shown in Table 2).

Table 2. Bias Analysis in AI Vs. Human Screening.

Feature	AI Screening	Human Screening
Potential Biases	Algorithmic bias due to biased training data, perpetuation of existing societal biases if not carefully designed and audited.	Subjectivity, unconscious biases based on gender, race, ethnicity, or other demographic factors.
Mitigation Strategies	Training AI on diverse datasets, regular auditing for fairness and transparency, careful design to minimize bias.	Awareness training, structured interviews, diverse interview panels.
Diversity Impact (Study Results)	Increase of 19 percentage points in candidate Net Promoter Score (NPS) among shortlisted candidates (potential for improvement).	Can vary significantly depending on the recruiter and the organization's diversity initiatives. Potential for lower diversity if biases are unchecked.
Objectivity	Aims for objectivity through data-driven decision-making, but requires careful monitoring to avoid unintended biases.	Prone to subjectivity, but can incorporate human judgment and contextual understanding.

5.2. Limitations and Future Research

This study, while providing valuable insights into the application of AI in recruitment and its impact on talent screening efficiency, is subject to certain limitations. The sample size, while adequate for initial analysis, could be expanded in future research to enhance the statistical power and robustness of the findings. Furthermore, the quality of the data used to train and evaluate the AI models is crucial. While efforts were made to ensure data accuracy and completeness, inherent biases within the historical data may have influenced the model's predictions and potentially perpetuated existing inequalities. The generalizability of the results is also a concern, as the study focused on a specific industry and organizational context. Different industries and organizational cultures may yield varying outcomes.

Future research should address these limitations by employing larger and more diverse datasets, incorporating bias detection and mitigation techniques, and conducting studies across multiple industries and organizational settings. Longitudinal studies are needed to explore the long-term impact of AI-driven recruitment on employee performance, job satisfaction, and employee retention. Specifically, research could investigate the correlation between AI-assessed candidate scores and subsequent performance metrics over a period of several years. Furthermore, the ethical implications of AI in recruitment, such as fairness, transparency, and accountability, warrant further investigation. Exploring the impact of AI on candidate experience and the potential for algorithmic discrimination is also crucial for ensuring responsible and equitable AI adoption in human resource management.

5.3. Ethical Implications and Bias Mitigation Strategies

AI recruitment, while promising increased efficiency, raises significant ethical concerns centered on fairness, transparency, and accountability. Algorithmic bias, stemming from biased training data or flawed algorithm design, can perpetuate and even amplify existing societal inequalities, leading to discriminatory hiring practices. For example, if the training data predominantly features a specific demographic group in successful roles, the AI might unfairly favor candidates from that group, disadvantaging individuals from other groups, even if they possess equivalent or superior qualifications.

Transparency is crucial; candidates deserve to understand how AI is used in the evaluation process and how their data is being processed. Black-box algorithms, lacking explainability, erode trust and hinder the ability to identify and rectify biases. Accountability mechanisms are also essential. When an AI system makes a biased decision, it is vital to determine who is responsible: the algorithm developer, the data provider, or the organization implementing the system.

Mitigation strategies include employing diverse and representative training datasets, regularly auditing algorithms for bias using metrics like disparate impact and equal opportunity, implementing explainable AI (XAI) techniques to understand decision-making processes, and establishing clear lines of responsibility for AI-driven decisions. Furthermore, human oversight remains paramount [7]. AI should augment, not replace, human judgment, particularly in final hiring decisions. Continuous monitoring and evaluation of AI recruitment systems are necessary to ensure ethical and equitable outcomes.

6. Conclusion

6.1. Summary of Findings

This research investigated the application and practice of AI recruitment in enhancing talent screening efficiency, revealing several key findings with significant implications for both HR professionals and the field of Artificial Intelligence. Firstly, our analysis demonstrated a statistically significant reduction in the time-to-hire metric when AI-powered screening tools were implemented. Specifically, the average time spent reviewing applications decreased by 43%, leading to faster recruitment cycles and reduced operational costs. Secondly, the study found that AI algorithms, trained on diverse datasets, can mitigate unconscious biases often present in traditional human screening processes. This resulted in a more diverse candidate pool and potentially improved the overall quality of hires, although continuous monitoring and refinement of the algorithms are crucial to prevent the perpetuation of existing biases present in the training data.

Furthermore, our research explored the impact of AI on the accuracy of candidate selection. While AI demonstrated proficiency in identifying candidates who met the minimum qualifications for a role, its ability to predict long-term job performance and cultural fit proved more nuanced. The predictive accuracy, measured by R^2 values ranging from 0.27 to 0.35, varied significantly depending on the specific role and the quality of data used to train the AI models. This highlights the importance of careful model selection, feature engineering, and ongoing performance evaluation.

Finally, the study examined the acceptance and integration of AI recruitment tools by HR professionals. While initial skepticism was observed, the majority of HR staff reported increased efficiency and improved decision-making capabilities after proper training and integration of the AI systems into their workflows. However, concerns regarding data privacy, algorithmic transparency, and the potential displacement of human recruiters remain, underscoring the need for ethical guidelines and responsible implementation strategies. The research contributes to a better understanding of the benefits and limitations of AI in recruitment, providing valuable insights for organizations seeking to leverage these technologies effectively.

6.2. Practical Recommendations

For organizations considering the adoption of AI recruitment technologies, a strategic and ethically grounded approach is paramount. Firstly, a clear articulation of recruitment goals is essential. Before implementing any AI solution, organizations must define specific, measurable, achievable, relevant, and time-bound (SMART) objectives. For example, instead of aiming to improve efficiency, a SMART goal might be to reduce time-to-hire by 15% within six months while maintaining candidate quality as measured by performance review scores.

Secondly, data quality and bias mitigation are critical. AI algorithms are only as good as the data they are trained on. Organizations must rigorously audit their historical data for biases related to gender, race, or other protected characteristics. Strategies to mitigate bias include data augmentation, algorithmic fairness constraints, and regular monitoring of AI output for disparate impact. The selection of appropriate features for model training should also be carefully considered to avoid inadvertently perpetuating existing inequalities.

Thirdly, transparency and explainability are crucial for building trust and ensuring accountability. Organizations should strive to use AI models that provide insights into their decision-making processes. Explainable AI (XAI) techniques can help to understand why a particular candidate was selected or rejected, allowing for human oversight and intervention. This is particularly important in sensitive areas such as candidate screening and selection.

Fourthly, continuous monitoring and evaluation are necessary to ensure that AI recruitment systems are performing as intended and are not having unintended consequences. Key performance indicators (KPIs) should be tracked regularly, and the system should be recalibrated as needed. This includes monitoring for bias, accuracy, and fairness.

Finally, human oversight remains essential. AI should be viewed as a tool to augment, not replace, human recruiters. Human recruiters can provide valuable context and judgment that AI systems may lack, particularly in assessing soft skills and cultural fit. A blended approach, combining the efficiency of AI with the empathy and judgment of human recruiters, is likely to yield the best results.

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