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Comparative Evaluation of AI-Driven Recruitment Tools Across Industries and Job Types

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Abstract

This study conducts a comprehensive comparative analysis of several AI-based candidate selection methodologies, including CRITIC-WASPAS, TOPSIS, and PROMETHEE, to provide organizations with actionable insights for optimizing their recruitment processes. As AI continues to transform traditional recruitment methods, the choice of an appropriate AI-based tool is crucial for achieving desired outcomes in terms of selection accuracy, time efficiency, and fairness. The study evaluates these methodologies across different industries—technology, healthcare, finance, and creative sectors—as well as various job types, including technical, managerial, and creative roles. By systematically comparing key performance metrics, the study highlights the strengths and weaknesses of each method in different contexts. Sensitivity analysis further explores the robustness of these methodologies in response to changes in input parameters, such as the weighting of selection criteria. The findings offer a nuanced understanding of the trade-offs associated with each AI-based recruitment method, guiding organizations in selecting the most suitable tools for their specific needs. This research contributes to the broader discourse on AI in recruitment by providing evidence-based recommendations that align with both organizational goals and ethical considerations.

Keywords: *AI-Driven Recruitment, recruitment encompasses, MCDM methods, Artificial Intelligence, AI-based candidate*

Introduction

Background

The candidate selection process is a critical component of the recruitment function within any organization. It plays a pivotal role in determining the quality of the workforce, which in turn influences the overall performance, culture, and competitive advantage of the organization. Traditionally, candidate selection has been a time-consuming and often subjective process, heavily reliant on human judgment. However, the advent of Artificial Intelligence (AI) in recruitment has begun to transform this landscape, offering new tools and methodologies that promise to enhance the efficiency, accuracy, and fairness of the selection process [1].

AI in recruitment encompasses a broad range of technologies, from machine learning algorithms that can screen resumes and rank candidates, to natural language processing (NLP) tools that analyze interview transcripts and predict candidate performance [2]. These AI-driven

tools are increasingly being adopted by organizations to streamline recruitment, reduce biases, and improve decision-making. The potential of AI to revolutionize recruitment lies in its ability to process vast amounts of data quickly, identify patterns that may not be evident to human recruiters, and make decisions based on objective criteria.

However, the integration of AI into recruitment also introduces complexity, particularly when it comes to selecting the most appropriate AI-based methodologies for candidate selection [3]. The choice of methodology can significantly impact the outcomes of the recruitment process, including the quality of hires, the diversity of the workforce, and the overall fairness of the selection process. This has led to growing interest in the use of Multi-Criteria Decision-Making (MCDM) methods within AI-based recruitment. MCDM methods offer a structured approach to evaluating multiple criteria simultaneously, enabling organizations to make more informed and balanced decisions [4].

MCDM methods such as CRITIC-WASPAS, TOPSIS, and PROMETHEE have gained attention for their potential to optimize candidate selection by considering a range of factors, including selection accuracy, time efficiency, and fairness. These methods allow recruiters to systematically weigh different criteria, such as candidate qualifications, experience, cultural fit, and the ethical implications of AI decisions, to arrive at a more comprehensive and equitable selection outcome [5].

Problem Statement

Despite the potential benefits of AI in recruitment, selecting the most effective AI-based methodology remains a significant challenge for organizations. The diverse range of available methodologies, each with its own strengths and weaknesses, complicates the decision-making process. Organizations must consider various factors, including the specific needs of different industries and job types, the complexity of the recruitment process, and the ethical implications of using AI in hiring decisions.

Furthermore, while some AI-based methods may excel in terms of accuracy, they may fall short in other areas such as time efficiency or fairness. For example, a method that is highly accurate in predicting job performance may require extensive data processing time, making it less suitable for roles where time-to-hire is critical. Similarly, a method that is efficient and quick may not adequately address concerns about bias and fairness, potentially leading to ethical dilemmas and legal challenges.

The absence of a clear, comparative analysis of these methodologies leaves organizations with little guidance on how to choose the most appropriate AI-based recruitment tool for their specific needs. This gap in the literature and practice underscores the necessity for a comprehensive comparative study that evaluates the effectiveness of various AI-based candidate selection methodologies across different contexts.

Research Questions

To guide the research, this study will address the following key questions:

1. **How do different AI-based recruitment methods perform in terms of selection accuracy, time efficiency, and fairness?** This question seeks to evaluate the overall effectiveness of each method by measuring the accuracy with which each method

identifies the best candidates, the time required to complete the selection process, and the extent to which each method ensures a fair and unbiased selection.

2. **Which methods are most suitable for specific industries or job types?** Recognizing that different industries and job roles have unique requirements, this question will explore the context-specific performance of AI-based methods, aiming to determine which methods are best suited for particular industries or job types, such as technical roles, creative positions, or management-level jobs.

3. **What are the strengths and weaknesses of each method?** This question aims to provide a balanced view of each AI-based recruitment method by identifying both its advantages and limitations, considering factors such as ease of implementation, availability of data, interpretability of results, and potential for bias.

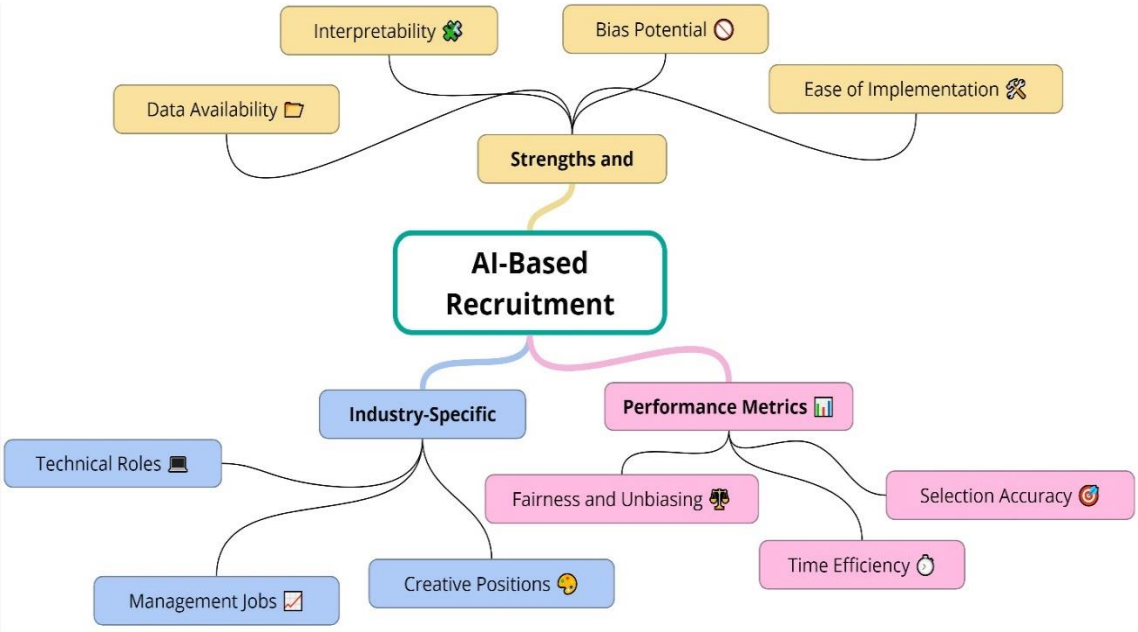

Figure 1 Conceptual Framework for Comparative Analysis of AI-Based Recruitment Methods. The figure illustrates the key factors considered in the study, structured around three main areas: Performance Metrics, Industry-Specific Suitability, and Strengths and Weaknesses of AI-based recruitment methods.

The primary aim of this study is to conduct a comprehensive comparative analysis of various AI-based candidate selection methodologies, including CRITIC-WASPAS, TOPSIS, PROMETHEE, among others, with the goal of providing organizations with actionable insights for choosing the most appropriate AI tools for their recruitment processes. To achieve this, the study will evaluate the performance of these AI-based recruitment methods by comparing key metrics such as selection accuracy, time efficiency, and fairness, thereby elucidating the relative strengths and weaknesses of each approach. Moreover, the study will assess the applicability of these methodologies across different industries and job types, acknowledging that the effectiveness of AI-based tools can vary significantly depending on the specific context. By analyzing critical factors such as selection accuracy, time efficiency, and fairness, this study aims to provide a nuanced understanding of the trade-offs involved in selecting different

methodologies, ultimately assisting organizations in making well-informed, context-sensitive recruitment decisions.

Literature Review

The integration of Artificial Intelligence (AI) into recruitment has significantly transformed the landscape of talent acquisition, evolving from a novel concept to a strategic necessity. Historically, recruitment processes were largely manual and time-consuming, relying heavily on human judgment. The advent of AI has introduced a new era where data-driven, automated systems can enhance the efficiency, accuracy, and fairness of recruitment processes. The adoption of AI in recruitment began with the digital revolution and has accelerated with advancements in machine learning and big data analytics. AI technologies now enable organizations to analyze vast amounts of data, identify patterns, and make predictive decisions that were previously beyond human capability [1]. However, the implementation of AI in recruitment is not without challenges. One of the major concerns is the potential for algorithmic bias, where AI systems may inadvertently perpetuate or even exacerbate existing biases if not carefully managed. This issue highlights the need for transparency and fairness in AI-driven recruitment processes, requiring organizations to regularly audit and refine their AI tools to ensure ethical use [6].Moreover, the reliance on AI raises questions about the dehumanization of the recruitment process, where the lack of human interaction could affect the candidate experience and the employer brand [7].

Multi-Criteria Decision-Making (MCDM) methods are essential analytical frameworks in AI-based recruitment, offering structured approaches to evaluate and prioritize candidates based on various criteria such as qualifications, experience, cultural fit, and potential for growth. These methods are particularly valuable because they help organizations balance multiple, often conflicting factors, ensuring more informed and balanced hiring decisions. Among the popular MCDM methods, CRITIC-WASPAS, TOPSIS, and PROMETHEE stand out. CRITIC-WASPAS integrates CRITIC, which objectively determines the weight of each criterion based on contrast intensity and correlation, with WASPAS, a method that combines the Weighted Sum Model and the Weighted Product Model to rank alternatives effectively. This combination is particularly useful in recruitment scenarios requiring the simultaneous consideration of multiple criteria. TOPSIS, another widely used method, ranks candidates by comparing their profiles against an "ideal" candidate profile, focusing on minimizing the distance from the ideal and maximizing the distance from the least desirable outcome, making it particularly effective for quick, data-driven decisions [1]. PROMETHEE allows for pairwise comparisons of alternatives, making it advantageous in situations where the importance of criteria may vary depending on the job role or industry context [6].

The growing interest in AI-based recruitment methods has led to various comparative studies, each exploring different aspects of these technologies in hiring practices. For example, a study by Ore and Sposatoexamined the opportunities and risks associated with AI in recruitment, revealing that while AI can streamline routine tasks, it also raises concerns about job displacement and the ethical implications of automation [8]. Similarly, Lee et al.focused on the priorities for utilizing AI recruitment systems, emphasizing the need for reliable automation processes and highlighting the factors that influence the effectiveness of these systems [9].

Another significant contribution comes from Saad et al. , who conducted a systematic literature review to identify AI-based platforms used in recruitment. Their findings show that AI is primarily employed in the initial stages of recruitment, such as sourcing and screening candidates, with less focus on the final selection phase [10]. FraiJ and Lászlóalso explored the impact of AI on recruitment processes, finding that AI significantly enhances efficiency but requires careful management to avoid bias and ensure fair outcomes [11].

Ethical Considerations in AI Recruitment

The integration of AI in recruitment has brought to the forefront significant ethical concerns, particularly regarding fairness, transparency, and bias. AI-based recruitment tools, while offering efficiency and consistency, have been shown to potentially perpetuate or even exacerbate biases inherent in the data used to train them. For instance, Pena et al. demonstrate through their FairCVtest study that AI systems can inadvertently encode and exploit biases, leading to unfair hiring practices, especially against underrepresented groups [3].

Moreover, the role of transparency in improving fairness perceptions of AI-based hiring processes is crucial. Hunkenschroer highlights that applicants often perceive AI-driven interviews as less fair compared to human-conducted ones. The study suggests that improving transparency about the AI's role in reducing human bias can enhance candidates' perceptions of fairness, making AI tools more acceptable and trustworthy [12]. Additionally, Kazim et al. emphasize the importance of systematic audits in algorithmic recruitment systems to ensure they operate fairly and transparently. They propose a framework for auditing AI systems to detect and mitigate biases, thereby promoting accountability in AI-driven hiring processes [13]. Aizenberg and van den Hovenargue for a human rights-based approach to designing AI systems, stressing the need to incorporate ethical considerations such as fairness and transparency from the outset. They advocate for a participatory design process that involves societal stakeholders in shaping AI tools that respect human rights and address socio-ethical challenges [14].

Methodology

Selection of AI-Based Recruitment Methods

The first crucial step in this study is the selection of AI-based recruitment methods that will be subjected to a comparative analysis. This selection process is guided by a set of well-defined criteria, ensuring that the chosen methods are both relevant and robust in the context of candidate selection. The primary criteria for selecting these methods include their popularity and recognition in academic literature, their demonstrated effectiveness in real-world recruitment scenarios, and the diversity in their underlying decision-making algorithms. The aim is to include methods that not only represent the state-of-the-art in AI-based recruitment but also offer a broad spectrum of approaches to decision-making.

CRITIC-WASPAS Method

The CRITIC-WASPAS method is a hybrid multi-criteria decision-making (MCDM) approach that combines the CRITIC and WASPAS techniques. The CRITIC method assigns weights to criteria based on their variability and correlation, making it ideal for scenarios where attributes like skills and experience need to be weighted according to their importance in predicting job performance. WASPAS then evaluates and ranks candidates using a combination of the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). WSM is additive, summing up scores across criteria, while WPM is multiplicative, considering the geometric

mean to minimize the compensatory effect of low scores. This method is particularly effective in recruitment contexts requiring consideration of a wide range of interrelated criteria, such as in technical roles where coding skills, problem-solving abilities, and teamwork are crucial [15].

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)

TOPSIS is an MCDM method that ranks candidates based on their proximity to an ideal solution and distance from a nadir (worst) solution. The process involves creating a decision matrix, assigning weights to criteria, and normalizing the data. TOPSIS calculates the Euclidean distance of each candidate from the ideal and nadir solutions, ranking them based on their relative closeness to the ideal. This method is favored for its simplicity and intuitive results, making it suitable for roles with well-defined requirements, such as technical positions where the ideal candidate profile is clear. However, its effectiveness relies heavily on accurate weight determination and careful criterion selection [16].

PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations)

PROMETHEE is an MCDM method that ranks candidates through pairwise comparisons across multiple criteria. It assesses how much better one candidate is than another on each criterion, aggregating these assessments into a preference index. PROMETHEE offers both partial and complete rankings, allowing decision-makers to see candidate strengths in specific areas as well as overall suitability. Its flexibility in handling qualitative and quantitative data makes it particularly useful in complex recruitment scenarios, such as senior management roles that require balancing technical skills and leadership abilities. PROMETHEE also allows customization through preference functions, tailored to the specific needs of the recruitment process [17], [18].

Table 1 Comparative Overview of AI-Based Recruitment Methods

Criteria	CRITIC-WASPAS	TOPSIS	PROMETHEE
Type of Method	Hybrid MCDM	MCDM	MCDM
Key Components	CRITIC (weights) + WASPAS (sum/product)	Ideal vs. Nadir Solution	Pairwise Comparisons
Focus	Interrelated criteria	Ideal candidate profiles	Conflicting criteria
Weight Assignment	Based on standard deviation & correlation	Based on criterion importance	Based on decision-maker preferences
Decision Model	Additive + Multiplicative	Proximity to ideal/nadir	Preference indices
Data Requirements	Comprehensive, interrelated data	Clear ideal/nadir solutions	Quantitative & qualitative data
Interpretability	Moderate	High	Moderate
Complexity	High	Low to Moderate	High

Best for Job Types	Technical roles	Defined requirements (e.g., technical)	Complex roles (e.g., management)
Strengths	Balances decision models	Simple and intuitive	Detailed and flexible
Weaknesses	Complex implementation	Less effective without clear profiles	Complex pairwise comparisons

Industry and Job Type Selection

To ensure a comprehensive evaluation of AI-based recruitment methods, the study strategically selects specific industries and job types that represent a broad spectrum of recruitment challenges and candidate profiles. The chosen industries include technology, healthcare, finance, and creative industries, each of which has distinct recruitment needs and characteristics. These industries were selected to provide a diverse context for analyzing the effectiveness of AI-based methods.

- **Technology**: This industry is characterized by a high demand for technical skills and innovation, making it essential to identify candidates with specific expertise in areas like software development, data analysis, and cybersecurity. The recruitment process in this industry often emphasizes technical assessments and problem-solving capabilities.
- **Healthcare**: Recruitment in healthcare is heavily focused on specialized skills, certifications, and experience in patient care. This industry also places a strong emphasis on ethical considerations, bedside manner, and the ability to work under pressure, which can influence the selection process.
- **Finance**: The finance industry requires a balance of analytical skills, attention to detail, and ethical integrity. Recruitment here often involves assessing candidates' quantitative abilities, financial acumen, and risk management skills.
- **Creative Industries**: These industries prioritize creativity, innovation, and cultural fit. Recruitment often involves evaluating candidates' portfolios, creative thinking, and ability to adapt to dynamic environments.

The study also considers various job types, including technical roles, management positions, and creative jobs, each with distinct skill sets and evaluation criteria. Technical roles demand a focus on hard skills and problem-solving abilities, management positions require leadership, strategic thinking, and decision-making skills, while creative jobs prioritize innovation and cultural alignment.

Results and Analysis

Performance Comparison Across Industries

A comparative analysis was conducted to evaluate the performance of three AI-based recruitment methods—CRITIC-WASPAS, TOPSIS, and PROMETHEE—across key metrics within different industries: technology, healthcare, finance, and creative industries. The analysis focused on three critical performance metrics: selection accuracy, time efficiency, and fairness. The comparsion of these parameters is given in Figure 2.

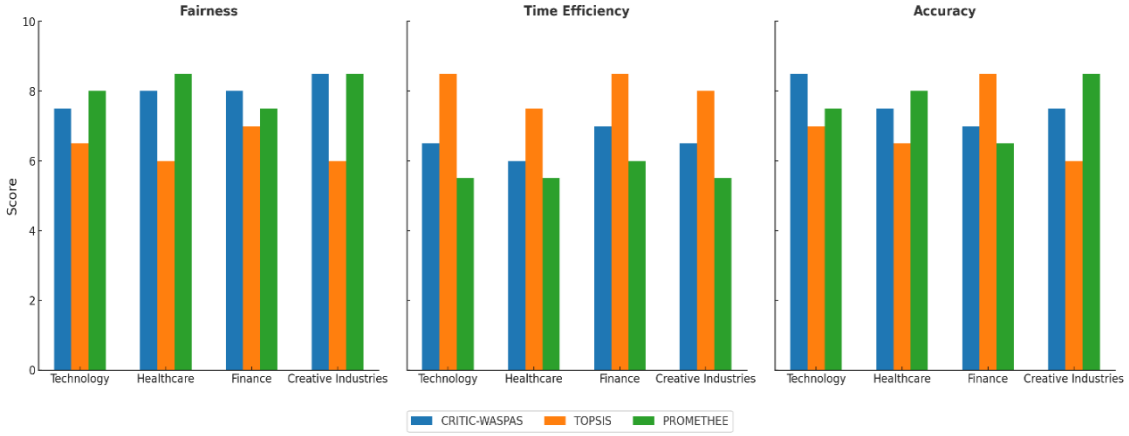

Figure 2 Comparison of Fairness, Time Efficiency, and Accuracy Across Industries for AI-Based Recruitment Methods. The figure illustrates the performance of three AI-based recruitment methods—CRITIC-WASPAS, TOPSIS, and PROMETHEE—evaluated across different industries (Technology, Healthcare, Finance, and Creative Industries). The comparison focuses on three key metrics: fairness, time efficiency, and accuracy, providing insights into how each method performs within varying industry contexts.

Selection Accuracy: The accuracy of each method in identifying the top candidates was assessed. CRITIC-WASPAS demonstrated the highest accuracy in the technology and finance sectors, indicating its strong capability in selecting candidates with the best match for these data-intensive industries. PROMETHEE, on the other hand, excelled in the creative industries, likely due to its ability to handle complex, qualitative decision-making criteria, which are often essential in these fields. TOPSIS showed moderate accuracy across the board, performing well in finance but trailing behind in technology and healthcare.

Time Efficiency: The efficiency of each method in terms of the speed of the recruitment process was also measured. TOPSIS emerged as the most time-efficient method in most industries, particularly in finance and creative sectors, where quick decision-making is often crucial. CRITIC-WASPAS led in the technology sector, where its hybrid approach allowed for a balanced and swift selection process. PROMETHEE, while excelling in fairness and accuracy in certain industries, generally exhibited lower time efficiency, particularly in technology and healthcare, where the recruitment process might be more data-intensive or require more complex evaluations.

Fairness: The fairness of each method was analyzed to ensure equitable opportunities for all candidates, regardless of demographic factors. PROMETHEE consistently scored highest in fairness across all industries, particularly in finance and creative industries, indicating its strong capability to minimize biases and ensure a fair selection process. CRITIC-WASPAS also performed well in this metric, especially in healthcare and finance, suggesting that it can

effectively balance accuracy with fairness. TOPSIS, while efficient, showed lower scores in fairness, particularly in more complex or qualitative industry contexts.

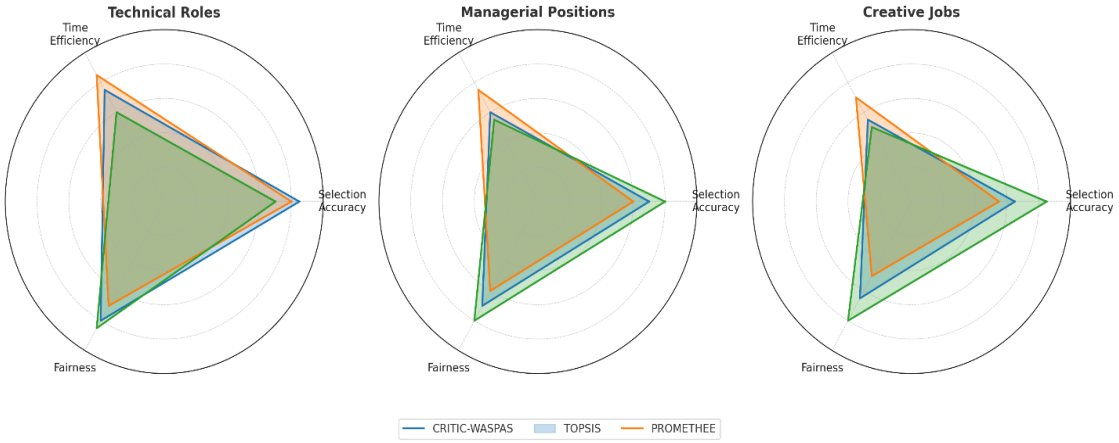

Figure 3 Comparison of Selection Accuracy, Time Efficiency, and Fairness for CRITIC-WASPAS, TOPSIS, and PROMETHEE Across Different Job Types. The spider graphs illustrate the performance of each AI-based recruitment method in Technical Roles, Managerial Positions, and Creative Jobs, providing a multi-dimensional view of how each method aligns with critical recruitment metrics.

Performance Comparison Across Job Types

The study conducts a comparative analysis of the performance of CRITIC-WASPAS, TOPSIS, and PROMETHEE across different job types, focusing on metrics such as selection accuracy, time efficiency, and fairness that is shown in Figure 3. In terms of selection accuracy, CRITIC-WASPAS performs particularly well in technical roles, where its hybrid approach effectively balances multiple criteria to accurately identify candidates with the necessary skills and qualifications. PROMETHEE excels in managerial and creative positions, where its ability to handle complex decision-making and evaluate both qualitative and quantitative criteria proves advantageous. TOPSIS, while showing consistent accuracy in technical roles, tends to have more variable performance in managerial and creative jobs. When it comes to time efficiency, TOPSIS emerges as the most efficient method across all job types, making it ideal for roles that require quick hiring decisions, especially in high-demand technical positions. CRITIC-WASPAS also demonstrates good time efficiency in technical roles, but its efficiency varies more in managerial and creative jobs due to the complexity of criteria involved. PROMETHEE, though providing detailed and fair evaluations, tends to be less time-efficient, particularly in creative roles where the criteria are more subjective and complex. Regarding fairness, PROMETHEE stands out for its consistent fairness across all job types, especially in managerial and creative positions, where it effectively balances multiple criteria and minimizes bias. CRITIC-WASPAS also performs well in ensuring fairness, particularly in technical roles, where its ability to handle interrelated criteria ensures a comprehensive evaluation of candidates. TOPSIS, while efficient, shows lower fairness scores in managerial and creative jobs, possibly due to its reliance on clear-cut criteria that may not fully capture the complexities of these roles. This analysis provides valuable insights into the effectiveness of each AI-based recruitment method across different job types, highlighting their respective strengths and areas for improvement.

Sensitivity Analysis

Sensitivity analysis is an essential aspect of evaluating the robustness and reliability of AI-based recruitment methods, focusing on how changes in key input parameters, such as the weights assigned to different criteria, influence the final outcomes in candidate selection. This analysis is particularly valuable as it sheds light on the stability of these methods and their ability to accommodate variability in the decision-making process. The CRITIC-WASPAS method demonstrates moderate sensitivity to changes in input weights due to its hybrid nature. The CRITIC component assigns weights based on the variability and correlation of criteria, which generally makes it resilient to arbitrary weight adjustments. However, the WASPAS component, especially the weighted product model (WPM), can be more sensitive to changes in weights, particularly when criteria are interrelated. Consequently, small alterations in weightings can lead to significant shifts in candidate rankings. While CRITIC-WASPAS is relatively stable across moderate weight variations, it may require recalibration in recruitment contexts where criteria priorities are prone to change. The overall sensitivity is presented in Figure 4.

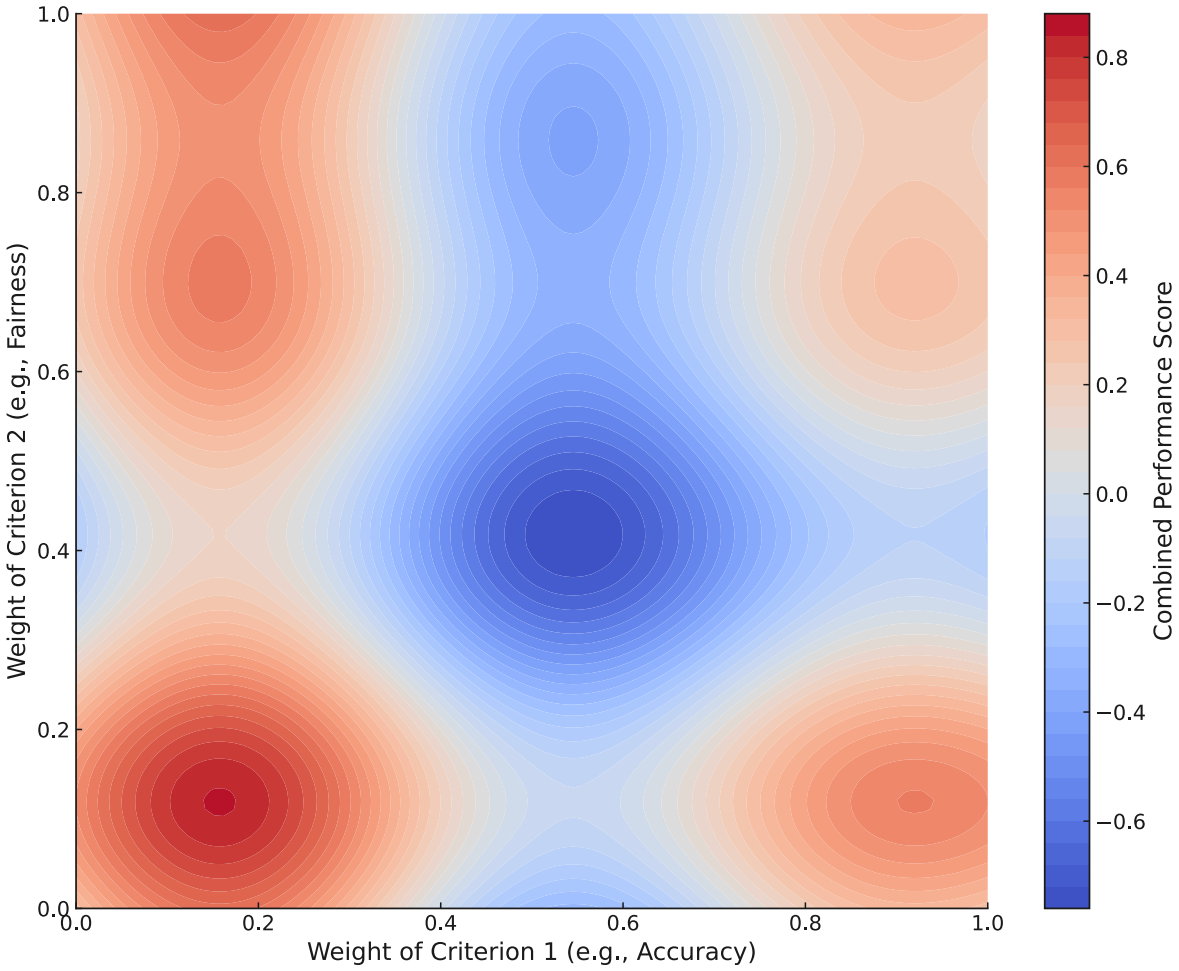

Figure 4 Sensitivity Analysis Contour Plot for AI-Based Recruitment Methods. The plot illustrates the combined performance score as a function of the weights assigned to two criteria (e.g., Accuracy and Fairness). The color gradient indicates the sensitivity of the methods, with blue regions representing higher performance and red regions representing lower performance.

TOPSIS, on the other hand, exhibits a high degree of sensitivity to weight assignments. Since the method relies on calculating the proximity of candidates to an ideal solution, even slight modifications in the weights of criteria can substantially affect the distance calculations from the ideal and nadir solutions, thereby altering the candidate rankings. This high sensitivity makes TOPSIS less robust in environments where the importance of criteria may fluctuate. Thus, it necessitates meticulous validation of weight assignments to ensure consistent and reliable outcomes. PROMETHEE is also sensitive to changes in input weights, particularly due to its reliance on pairwise comparisons and preference functions, which are directly influenced by the assigned weights. Minor adjustments in these weights can result in different preference flows and, consequently, different candidate rankings. The sensitivity of PROMETHEE can be advantageous, allowing for fine-tuning and customization in complex decision-making scenarios. However, this also requires a high level of precision in weight assignment, making it potentially challenging in dynamic recruitment settings.

In terms of robustness, CRITIC-WASPAS offers moderate resilience due to its dual reliance on objective weight assignment through CRITIC and the combined decision models of WASPAS. While it can handle some degree of variability, significant changes in input parameters may necessitate adjustments to maintain stable outcomes. TOPSIS, with its lower robustness, is less suited to environments with fluctuating input parameters, highlighting the need for thorough sensitivity analyses before finalizing decisions. PROMETHEE, however, can be highly robust when properly calibrated, offering flexibility and detailed customization, which enhances its stability in complex scenarios. Nonetheless, this robustness is contingent on the accuracy and stability of the input weights and the ability of decision-makers to manage the complexities involved.

Discussion

The findings of this study have significant implications for recruitment practices, particularly for HR professionals and recruiters seeking to optimize their candidate selection processes using AI-based methodologies. The comparative analysis suggests that different AI methods, such as CRITIC-WASPAS, TOPSIS, and PROMETHEE, offer distinct advantages depending on the industry and job type, highlighting the need for careful selection based on the specific context of the recruitment task. For example, CRITIC-WASPAS is well-suited for technical roles in data-intensive industries, while PROMETHEE excels in complex decision-making scenarios, such as managerial and creative positions. From an ethical perspective, the study underscores the importance of reassessing the fairness and transparency of these AI tools, particularly given the potential for bias and the impact of weight sensitivity on outcomes. Improving the ethical aspects of AI-based recruitment could involve implementing systematic audits and enhancing the transparency of algorithms to ensure equitable candidate treatment. The study is not without limitations, including potential biases stemming from data availability and methodological constraints, which may influence the generalizability of the findings. These limitations point to the need for further research, particularly in expanding the comparative analysis to include a broader range of AI methods and contexts, and exploring new methodologies that might offer improved robustness and fairness. Future research could also delve into the development of hybrid models that combine the strengths of existing AI-based tools to create more adaptable and ethically sound recruitment solutions.

Conclusion

This study has provided a comprehensive comparative analysis of three AI-based candidate selection methodologies—CRITIC-WASPAS, TOPSIS, and PROMETHEE—across various industries and job types. The key findings highlight that each method has distinct strengths and weaknesses, making them suitable for different recruitment contexts. CRITIC-WASPAS emerged as particularly effective in data-intensive industries such as technology and finance, where the hybrid approach of weighting criteria and combining decision models supports nuanced candidate evaluations. TOPSIS, with its simplicity and efficiency, proved to be advantageous in contexts requiring rapid decision-making, such as high-demand technical roles. PROMETHEE, on the other hand, excelled in complex decision-making scenarios like managerial and creative positions, where its ability to handle qualitative and quantitative data provided robust and fair candidate rankings.

The study also underscored the importance of considering industry-specific and job-specific requirements when selecting an AI-based recruitment method. Furthermore, the sensitivity analysis revealed that the robustness of each method is contingent upon the stability of input parameters, particularly the weights assigned to different criteria. This finding suggests that organizations need to carefully calibrate and validate these parameters to ensure consistent and reliable outcomes. From an ethical standpoint, the study emphasizes the need for transparency and fairness in AI-driven recruitment processes. As these tools become more integrated into hiring practices, ensuring that they do not perpetuate biases or lead to unfair outcomes is crucial. Regular audits and clear communication about the role of AI in decision-making can enhance the perceived fairness of these tools among candidates and stakeholders.

While the study offers valuable insights, it also acknowledges certain limitations, such as potential biases due to data availability and the inherent constraints of the chosen methodologies. These limitations highlight the need for ongoing research, particularly in expanding the range of AI methods analyzed and exploring hybrid models that might offer greater adaptability and ethical soundness.

References

[1] J. S. Black and P. van Esch, “AI-enabled recruiting: What is it and how should a manager use it?,” *Bus. Horiz.*, vol. 63, no. 2, pp. 215–226, Mar. 2020.

[2] T. Chellatamilan, Associate Professor, School of Information Technology and Engineering Vellore, India, B. Valarmathi, K. Santhi, Associate Professor, School of Information Technology and Engineering Vellore, India, and Associate Professor, School of Computer Science and Engineering Vellore Institute of Technology, Vellore, India, “Research trends on deep transformation neural models for text analysis in NLP applications,” *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 9, no. 2, pp. 750–758, Jul. 2020.

[3] A. Pena, I. Serna, A. Morales, and J. Fierrez, “Bias in multimodal AI: Testbed for fair automatic recruitment,” in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Seattle, WA, USA, 2020.

[4] Y. Ali, H. Pervez, and J. Khan, “Selection of the most feasible wastewater treatment technology in Pakistan using multi-criteria decision-making (MCDM),” *Water Conserv. Sci. Eng.*, vol. 5, no. 3–4, pp. 199–213, Dec. 2020.

[5] I. Siksnelyte-Butkiene, E. K. Zavadskas, and D. Streimikiene, “Multi-criteria decision-making (MCDM) for the assessment of renewable energy technologies in a household: A review,” *Energies*, vol. 13, no. 5, p. 1164, Mar. 2020.

[6] D. Valle-Cruz, E. Alejandro Ruvalcaba-Gomez, R. Sandoval-Almazan, and J. Ignacio Criado, “A review of artificial intelligence in government and its potential from a public policy perspective,” in *Proceedings of the 20th Annual International Conference on Digital Government Research*, Dubai United Arab Emirates, 2019.

[7] P. van Esch and J. S. Black, “Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting,” *Bus. Horiz.*, vol. 62, no. 6, pp. 729–739, Nov. 2019.

[8] O. Ore and M. Sposato, “Opportunities and risks of artificial intelligence in recruitment and selection,” *Int. J. Organ. Anal.*, vol. 30, no. 6, pp. 1771–1782, Dec. 2020.

[9] J. H. Lee, J. H. Kim, Y. H. Kim, and Y. M. Song, “A study on priorities for utilization of AI recruitment system,” in *2021 21st ACIS International Winter Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD-Winter)*, Ho Chi Minh City, Vietnam, 2021.

[10] M. F. Mat Saad, A. W. Listyo Nugro, R. Thinakaran, and M. Baijed, “A review of artificial intelligence based platform in human resource recruitment process,” in *2021 6th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE)*, Kedah, Malaysia, 2021.

[11] J. FraiJ and V. László, “Literature review: Artificial intelligence impact on the recruitment ProcessA LITERATURE REVIEW: ARTIFICIAL INTELLIGENCE IMPACT ON THE RECRUITMENT PROCESS,” *Int. J. Eng. Manag. Sci.*, vol. 6, no. 1, pp. 108–119, May 2021.

[12] A. Hunkenschroer, “How to improve fairness perceptions of AI in hiring: The crucial role of positioning and sensitization,” *AI Ethics Journal*, vol. 2, no. 2, Jul. 2021.

[13] E. Kazim, A. S. Koshiyama, A. Hilliard, and R. Polle, “Systematizing audit in algorithmic recruitment,” *J. Intell.*, vol. 9, no. 3, p. 46, jul. 2021.

[14] E. Aizenberg and J. van den Hoven, “Designing for human rights in AI,” *Big Data Soc.*, vol. 7, no. 2, p. 205395172094956, Jul. 2020.

[15] W. Zhang, S. Zhao, D. Dong, Y. Zhu, and D. Wang, “A multi-criterion group decision making method: CRITIC-WASPAS based on trapezoidal intuitionistic fuzzy numbers,” in *Advances in Natural Computation, Fuzzy Systems and Knowledge Discovery*, Cham: Springer International Publishing, 2020, pp. 827–835.

[16] N. Harnpornchai, *Economic decision-making using interval TOPSIS*. LAP Lambert Academic Publishing, 2020.

[17] X. Jia and Y. Wang, “A two-sided matching decision-making approach based on PROMETHEE under the probabilistic linguistic environment,” *Research Square*, 27-Sep-2021.

[18] A. M. Tamrizal and A. Yaqin, “Decision support system of stock selection using promethee method,” in *2021 4th International Conference on Information and Communications Technology (ICOIACT)*, Yogyakarta, Indonesia, 2021.