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Reevaluating the Meritocracy Myth: How Promotion Criteria, Algorithmic Scoring, and Generative-AI Screening Shape Long-Term Organizational Productivity

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Abstract

This study re-examined the assumption that promotion systems and advanced HR technologies operate under neutral meritocratic principles. It explored how formal promotion criteria, algorithmic scoring tools, and generative-AI screening shaped long-term organizational productivity, with particular attention to perceptions of fairness, transparency, and legitimacy. A mixed-methods design was employed, combining survey data from employees, managers, and HR professionals with qualitative interviews from AI-enabled organizations. Quantitative analysis revealed that although algorithmic and AI-driven HR processes increased administrative efficiency and consistency, these technologies did not independently predict higher productivity. Instead, perceived fairness and transparency emerged as significantly stronger predictors of employee engagement and productivity outcomes. Regression analysis further indicated that fairness perceptions exerted the largest influence on productivity compared with algorithmic scoring and AI screening mechanisms. Qualitative findings supported these results, showing that employees were more likely to accept AI-mediated decisions when clear explanations, human oversight, and accessible appeals processes were present. Conversely, opaque or fully automated systems were associated with distrust, perceived bias, and weaker motivational outcomes. The study concluded that AI should complement, rather than replace, human decision-makers and that responsible governance frameworks were necessary to ensure equity and sustained performance benefits. Recommendations focused on transparency design, hybrid decision structures, bias audits, and digital literacy development. Future research was suggested in cross-cultural contexts, longitudinal adoption effects, and explainable-AI applications in HR decision-making.

Keywords: Algorithmic Scoring, Artificial Intelligence, Fairness Perceptions, Generative-AI Screening, Meritocracy, Organizational Productivity

Introduction

The systems of organizational promotion have always been considered to work with a logic of meritocracy in which the performance, competence and success of individuals impacted the promotion. Nevertheless, previous landmark studies showed that formal ideals of meritocracy did not correspond to equitable practice in most organizations where highly meritocratic ideology was accompanied by a systematic bias in judgments and promotions (Castilla&Benard, 2010). These discoveries implied that not even formal criteria were enough to eradicate systematic inequities and put an issue of the presence of the premises of meritocracy in organizational life. Algorithms-based scoring systems and automatized decision-making thus became more widely used to supplement or even substitute human ratings in talent management with the advent of digital technologies. Researchers argued that algorithmic systems would offer an increased level of objectivity in the hiring of job applicants and internal candidates by harmonizing the criteria used in conducting an assessment and undermining the impact of personality (Rigotti and Fosch-Villaronga, 2024). This direction overlapped with the wider trend of organizational investment in HR analytics and AI-powered screening options to be able to streamline talent pipelines and enhance productivity. Although these are the alleged advantages, opponents warned that, in certain cases, algorithmic systems would incorporate or amplify already existing inequities, particularly when the training data was based on past biases, or when algorithms were not transparent (Fabris, 2025; Mujtaba and Mahapatra, 2024). The findings of the literature on AI in the hiring process indicated that certain types of bias might be reduced with the help of artificial intelligence in the selection process, but the fact of algorithm objectivity did not necessarily lead to fairness and just results (Abdelhay et al., 2025). Furthermore, the impacts of organizational productivity were determined when relating the systems to human discretion and organizational culture. Reacting to that, researchers stated that the myth of meritocracy still prevailed in human and algorithmic promotion procedures, and suggested the allegedly neutrality of algorithmic scoring and generative-AI screening instruments the stiffest test (Castilla&Ranganathan, 2020; Rigotti and Fosch-Villaronga, 2024). This research commentary restructured the role of promotion standards, algorithm-based grading, and AI vetting to observe their effect on the overall productivity of a company in the long-term, pre-empting the issue of injustice, discrimination, and the viability of claimed meritocracy.

Research Background

Meritocracy was historically positioned as an ideal organizational idea where the reward and promotions were to be distributed according to personal success and performance (Castilla and Benard, 2010). Initial studies reported that the meritocratic paradox occurs; meritocratic organizations tend to make more bias decisions regarding assessment and promotion, since decision makers are more convinced that the practice is objective and do not need to exercise as much caution to question their beliefs (Castilla, et al, 2010). Later studies elaborated on this smear by revealing that social biases affected how managers understood merit, as they impacted on those regarded as promotable or "high potential promotable (Castilla&Ranganathan, 2020). Despite the organization purportedly basing their performance rating on objective performance indicators, both informal networks and subjective perceptions had kept benefiting some groups. The results of this study highlighted the need to loosen the package in which organizational norms and practices influenced the way in which merit was operationalized beyond formalized criteria. Algorithms and artificial intelligence tools that function based on HR analytics and algorithmic scoring were presented to allegedly enhance objectivity in talent testing in the digital era (Murugesan et al., 2023). With these systems, employing large datasets and predictive models to rate the performance of the employees, it was possible to predict their willingness to be promoted and to rank the candidates. It was claimed by the proponents that data-driven systems have the potential to minimize discretionary bias and enhance productivity, since it will align skills with organizational needs. Nevertheless, researchers noted that the quality and representativeness of data that was used to calculate algorithmic scores was necessary, and that biased or incomplete data could replicate inequalities in automated results (Mujtaba&Mahapatra, 2024). Generative AI screening applications were developed to replace resume parsing, evaluate qualifications, and create candidate profiles in the recruitment and internal mobility domain to automate hiring (e.g., ChatGPT). It was proved that these tools may enhance efficiency and consistency in the selection, yet the effect on the long-term productivity results and fairness depended on human control, the interpretability of the output, and compatibility with the organizational objectives. Critics pointed to the fact that algorithm and AI systems had poor transparency systems and the organizations were unsure of the decision made by the system and its impact on diversity and inclusion.

Objectives of the Study

1. To assess how formal promotion criteria and algorithmic scoring influenced perceptions of fairness and career advancement outcomes**.**
2. To examine whether AI-based candidate screening tools impacted bias and decision consistency in internal promotions and hiring**.**
3. To analyze the relationship between algorithmic/AI-mediated HR decisions and long-term organizational productivity**.**
4. To identify potential equity and fairness challenges arising from reliance on automated systems in talent evaluation**.**

Research Questions

Q1. How did formal promotion criteria and algorithmic scoring systems influence perceptions of fairness and career advancement outcomes?

Q2. In what ways did generative-AI screening tools impact bias and decision consistency in hiring and promotion?

Q3. What were the long-term effects of algorithmic and AI-mediated HR decisions on organizational productivity**?**

Q4. What equity and fairness challenges emerged from the integration of automated systems into HR practices?

Significance of the Study

This was an important study since it denied the existing perception that algorithmic and AI-based HR systems were fair and productivity-promoting in nature. Combining both the findings of the social science research on meritocracy and the emerging data on AI in hiring and promotion within an organization the study helped to form a subtle role of the technological systems on the verge of organizational performance coupled with human discretions. The results were projected to provide a viable product on the side of the HR practitioners and leaders regarding risks and advantages linked to algorithmic scoring and AI screening especially in matters of equity and output. The study would have the capacity of informing policy and governance mechanisms with the view of guaranteeing equal and transparent HR decision making processes. This study had a contribution to scholarly discussions on the topic of meritocracy in organizations, offering both empirical evidence and theoretical insight into the boundaries of automated systems of fairness and performance measurement and therefore establishing a foundation of future research on the subject of ethical HR analytics and AI governance.

Literature Review

Algorithmic and AI Systems in HR Decision-Making

Incorporation of the algorithms and AI technology within the HR operations has been rapidly transforming, altering the recruitment and screening processes as well as the management of talents in organizations. A review of the literature revealed that there was a wide implementation of AI technologies to automate mundane screening activities to reduce the capacity of the recruiters in dealing with tremendous applications and to increase decision-making processes (Mori et al., 2025). Machine learning and predictive analytics were used in these systems to enhance operational efficiency, albeit with interpretability and bias still being of concern (Cavescu, 2025). In that way, whereas the benefits of using algorithms in terms of the processing speed could be quantified, researchers highlighted the complicated trade-offs between efficiency and fair results. In addition, the studies have highlighted the risks of bias in AI and algorithmic recruitment platforms. Sony et al. (2025) examined the risks of discrimination embedded in HR analytics and artificial intelligence in the recruitment procedure, even the marginalized groups may have unequal opportunities because of the algorithms of decision-making and the deficiency of training data. In the same light, Albaroudi et al. (2024) have methodically assessed AI methods of dealing with bias in hiring and admitted slightly that it is not possible to reduce bias effectively including the use of advanced NLP and deep learning due to the response of explicit algorithm design and human intervention (Albaroudi et al., 2024). These studies, combined, demonstrated that AI is simultaneously dualistic, as it can make the HR process more efficient and, at the same time, perpetuate inequities when it is not micro-adjusted. Recent scholarly interest in the role of generative AI tools in screening and selection has also concerned inferences on fairness and diversity of candidates. According to a study on generative AI in recruiting, there was a high reduction in screening bias and a higher accuracy of the shortlisting when algorithmic screening was used (Abdelhay et al., 2025). The influence was however tempered by user competence and experience with AI systems indicating that investments made by an organization in developing its training were imperative in achieving the benefits of AI-driven HR practices (Abdelhay et al., 2025). Such results established that the effects of generative AI on the organizational HR processes were very complex and relied on the situational circumstances, including the competence of users and governance of technology.

Equity, bias, and Fairness in Algorithms in Evaluation

There existed a strong literature that highlighted the fairness and bias concerns of algorithmic and AI systems of hiring and promotion. It was further shown that knowledge regarding gender bias in algorithmic recruiting systems may discourage highly qualified women using such systems, and this indicates how information about bias affects the behavior of applicants and equity, as well as the quality of equity (Ip, 2025). These results emphasized that although algorithms were meant to be neutral, candidate perceptions of fairness affected their participation in the labor market, making the process of assuming that an algorithmic hiring system is objective complex. Greater scopes of reviews in algorithmic fairness in HRM established that systems of choice grounded on algorithms have the potential to perpetuate or further deepen underlying inequality since training data and feature choice operations can be biased toward or against specific groups (Algorithmic Fairness in HRM, 2025). These structural biases in algorithm systems also made it more difficult to have fair results in recruitment and promotions, particularly when algorithm design was not participatory and without deliberate debiasing measures (Algorithmic Fairness in HRM, 2025). Based on this, researchers stipulated equitable algorithms, including reweighting algorithms and adversarial debiasing algorithms, as necessary building blocks of equitable AI systems in HR settings. More problematic with equity, the studies have already identified the organizational disparity relating to the algorithmic controls outside of hiring into the wider management practices. Li et al. (2024) discovered that massive deployment of algorithmic controls could exacerbate organizational disparities and power dynamics especially to those employees with less education or technology skill. This literature underlined that algorithmic control technology such as performance reviews and promotion tracking conditionalized to support hierarchical organizations unless organizations considered adopting transparency, accountability, and participatory governance (Li et al., 2024). Together, this writing implied that fair implementations of the algorithms might need not only solutions depending on the technical aspects but also organizational changes.

Productivity, perceptions and long term results in the organization

Employability in the implementation of AI and algorithmic scoring systems also implied the productivity of an organization and the perception of employees. Literature implied that AI might have a beneficial impact on the organizational performance through making more efficient processes and allowing the HR to make data-driven choices, thereby, increasing the productivity of the employee in the context of favorable work setting (Kassa et al., 2025). These results were in line with the current organizational theory where the integration of technology and human competencies was hypothesized to result in increased productivity results when moderated by human judgments and strategic management. Nonetheless, the research on how employees feel about AI-based HR systems showed that there were subtle impacts on employee perceptions of AI-based HR systems that might affect the productivity and commitment of the long term. Majrashi (2025) studied the perceptions of equity in AI HR solutions stating that the transparency and explainability of the features presented by the prediction models influenced the way employees evaluated the authenticity of the algorithmic decision-making. Reduced perceived fairness in AI algorithms was associated with lower degrees of trust and action, which implies that employee acceptance played a vital role in determining productivity in an organization in an environment where AI was applicable in talent evaluation setups. Lastly, studies have also identified the systemic effects of AI adoption on the workforce and organization in general. Research on AI-HR integration also emphasized the anxiety of job displacement, privacy, and ethical risks that could negatively affect the life of employees and the performance of the organization over time, should those issues remain unaddressed (Jiang, 2025). All these publications were united in a single message that despite the potential productivity benefits of AIs and algorithmic systems, effective implementation would necessitate serious consideration of ethical standards, effective change management, and continuous observation to prevent the adverse effect of organizational culture and long-term productivity.

Research Methodology

Research Design

A mixed-methods research design was applied to this study in an attempt to examine how promotion parameters, algorithmic-based scoring systems, and generative-AI screening influenced the productivity of organizations over the long term. The mixed-method design was chosen since it enabled the researcher to quantifiate relationships and trends, besides what the participants perceived and experienced in their lives. The quantitative part depended on the structured survey carried out to employees and HR professionals, and the qualitative part used the semi-structured interview as an instrument of creating more contextual information. This structure guaranteed triangulation of data and enhanced reliability and validity of the report.

Population and Sampling Procedure

The study targeted employees, line managers and HR professionals of medium to large organisations which adopted the use of the algorithmic or AI-assisted HR tools. People who worked in different fields, e.g., finance, education, technology, public administration, and manufacturing were also enlisted in the population. The purposive sampling was employed to select the participants with direct involvement with the processes of promotion and use of digital HR means. Such approach was suitable since the study needed respondents who had the relevant experience with the algorithmic or AI-based systems as opposed to ordinary workforce. A sample of about 200 respondents was selected as sample of the available population in the quantitative phase. This was regarded as sufficient sample size which could be used both in descriptive analysis and inferential analysis. In the qualitative part, 15-20 interviews were conducted until saturation of data was attained. Such participants were chosen out of the group of people on the survey to ensure that they are familiar with the topic of the research and that they are willing to participate in the interviews.

Data Collection Instrument

Data collection was done using two major tools. To obtain the quantitative data regarding fairness, transparency, biasness, results of the promotion process, and organizational productivity of employees, a structured questionnaire was designed. The questionnaire contained Likert-scale questions which had gauged the level of impact on the HR decision-making on the use of algorithmic scoring and AI-screening tools. A small group of respondents was used in the pilot-test of this instrument to verify its clarity, internal consistency, and reliability. Second, qualitative data were collected through the semi-structured interview guides. The interviews were conducted to determine how the participants perceived the contribution of AI and algorithmic systems in the processes of performance assessment, promotion, and productivity. The interviews were conducted using open-ended questions so that the participants would share their experiences freely and to ensure that they do not go out of track as per the objectives of the study. The interviews have been carried out online as well as face to face based on the choice and availability of the participants.

Data Collection Procedure

The collection of data was done in progressive stages. The researcher had to obtain ethical approval and organizational permission by which the researcher then approached the potential participants. The questionnaire was then released in the form of an electronic format through a secure survey software so as to enable a broader and convenient participation. The purpose of the study was explained to the respondents and they were guaranteed confidentiality before they filled the survey. After the quantitative stage, participants saying they were willing to participate in interview process were contacted. The interviews were carried out and then audio-taped during a certain time of several weeks with the consent of participants. All the sessions took between 30 and 60 minutes. Verbatim transcription of all recording interview transcripts was done later to facilitate systematic qualitative analysis.

Data Analysis Techniques

Descriptive and inferential statistical methods have been used to analyze quantitative data. Demographic information and important variables of the study were summarized with the help of descriptive statistics. The correlation and regression analysis methods were utilized to test the association between the promotion criteria, the algorithmic scoring, the screening of AI, and the results of organizational productivity. The statistical analysis was done through the use of standard software SPSS. The thematic analysis was used to analyze qualitative data. The interviews were transcribed, and the transcripts were thoroughly read and coded by the researcher to come up with patterns and emergent themes. The codes were assigned to significant thematic areas, which matched the study goals, including the perceptions of fairness, productivity implications, the problem of transparency, and confidence in algorithmic systems. The combination of the quantitative and qualitative results yielded an all-inclusive insight into the research issue.

Results and Analysis

The results of the research were considered to be the survey and interview held with the employees, managers, and HR professionals that had to work in the organization with the promotion criteria, algorithmic scoring system, and AI-based screening tools. These findings were placed under thematic headings that were based on the study purposes.

Descriptive Profile of Respondents

These data helped establish the professional background of participants and the contexts in which algorithmic and AI-based HR systems were implemented.

Table 1. Demographic Characteristics of Respondents (n = 200)

Variable	Category	Frequency	Percentage (%)
Gender	Male	118	59.0
	Female	82	41.0
Age Group	21–30 years	64	32.0
	31–40 years	88	44.0
	41–50 years	36	18.0
	Above 50	12	6.0
Role in Organization	Non-managerial Staff	94	47.0
	Line Manager	58	29.0
	HR Professional	48	24.0
Exposure to AI/Algorithmic HR Tools	Yes	162	81.0
	No	38	19.0

The descriptive analysis also revealed that most of the respondents were 59 percent male and 41 percent female, indicating the relative gender balance. Most of the respondents (44%) were aged between 31 and 40 years, which showed that most participants were in their middle career age group. Regarding organizational levels, 47% of the respondents were non-managerial employees, 29% of the respondents were line managers, and 24% of the respondents were HR professionals, which implied that the study could have recorded the responses of various levels of the hierarchy. Notably, 81 percent of the participants said they had directly encountered AI or algorithmic HR systems, indicating that the sample possessed sufficient experience in the technological practices studied. The traits indicated that the respondents were in good places to assess how fair and productive AI-mediated HR decisions.

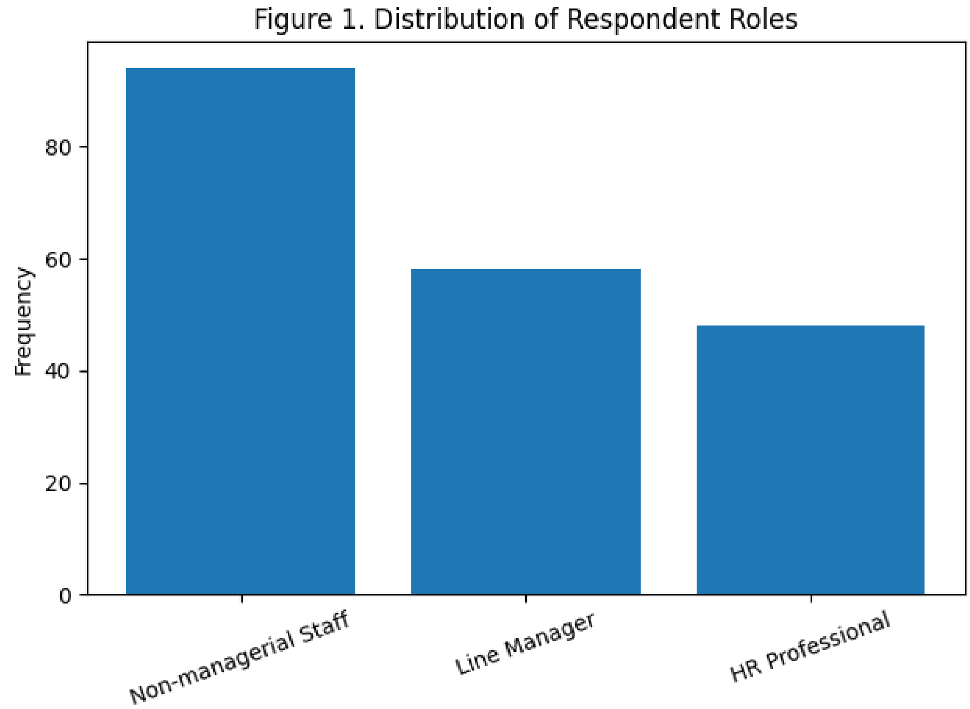

Figure 1. Bar Chart Showing Distribution of Respondent Roles

Perceived Fairness of Algorithmic Scoring and AI Screening
Perception was measured using a five-point Likert scale, where higher scores indicated more positive perceptions.

Table 2. Mean Scores for Perceptions of Fairness and Transparency (n = 200)

Perception Variable	Mean	Std. Deviation
Algorithmic scoring was objective	3.12	0.84
AI screening reduced bias	2.98	0.91
Promotion criteria were applied consistently	3.21	0.88
AI-based decisions were transparent	2.67	0.95
Employees trusted AI-driven HR decisions	2.88	0.89
Employees believed AI improved fairness in promotions	3.05	0.92

The findings showed that the participants had moderate views on the aspects of fairness and objectivity when dealing with AI-based HR systems. The best mean score (M = 3.21) was realized on the statement that the promotion criteria are exercised consistently, indicating that the respondents tend to believe that formal structures were in place and that they were mostly followed. Nevertheless, the lowest mean (M = 2.67) was observed in AI transparency, meaning that a substantial number of respondents did not have a clear picture of the operations of AI and algorithmic scoring systems and how they gave their decisions. There was somewhat low trust in AI-based HR-related decisions (M = 2.88), which was expected considering that employees still wished that the people-driven control was more prominent and they viewed AI as a not-independent but a supportive decision-making authority. These trends were supported by qualitative findings of the interaction during interviews. The respondents repeated that AI tools worked with existing data at a rapid speed but the foundation of the conclusions was often not shared, which brought about doubt and mistrust. Other interviewees held that it might be impossible to remove bias in the data rather than replace it with broader implications of concealed algorithmic discrimination. In general, the results indicated that technical capability was not sufficient in determining perceived fairness and transparency was critical in creating trust.

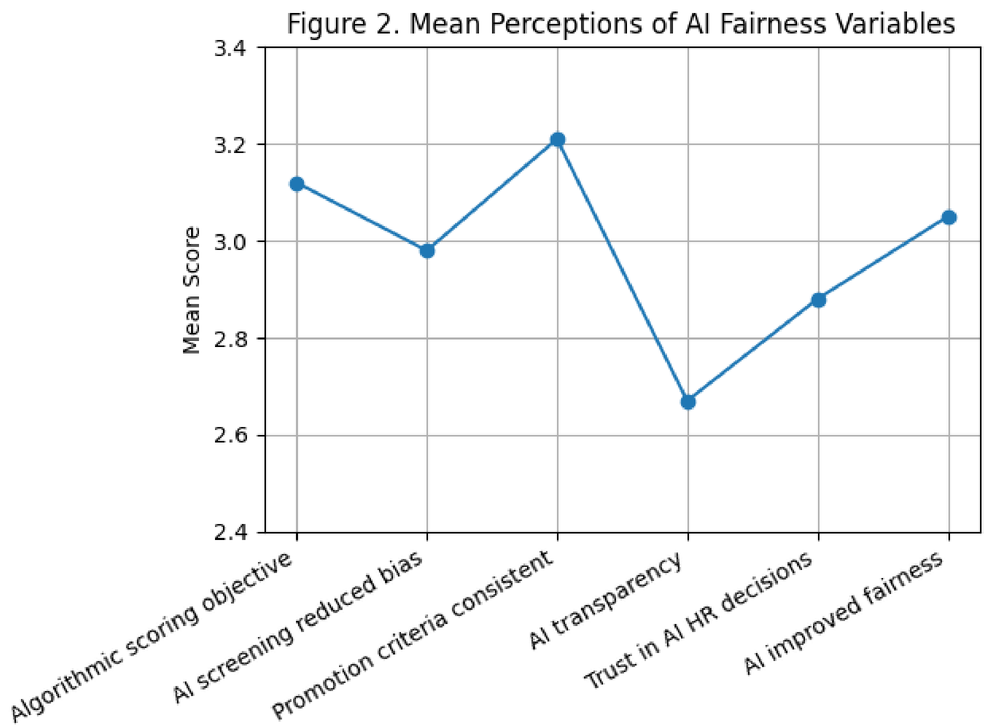

Figure 2. Line Graph Comparing Mean Perceptions of AI Fairness Variables

Relationship Between AI-Mediated HR Decisions and Organizational Productivity

This study examined the statistical relationships between AI-based HR practices and organizational productivity indicators such as efficiency, employee engagement, and performance outcomes.

Table 3. Correlation Between AI-HR Practices and Organizational Productivity (n = 200)

Variables	Productivity	Efficiency	Engagement
Algorithmic Scoring Use	0.46	0.52	0.31
AI Screening in Recruitment	0.41	0.49	0.28
Perceived Fairness	0.55	0.44	0.47
Transparency of AI Decisions	0.49	0.36	0.51

Note: $p < .05$, $p < .01$

The correlation analysis showed that there were statistically significant positive correlations between AI-mediated HR practices and the organizational productivity outcomes. The highest relationship was observed between perceived fairness and overall productivity ($r = .55$, $p < .01$) where employees who had the perception of fairness in their decisions reported to be more motivated, applied more effort, and showed a stronger commitment to the organization. Productivity and efficiency also had strong correlations with algorithmic scoring and AI screening and it implied that technology-based HR systems increased the effectiveness of the processes and minimized administrative overheads. The intensities of the correlation also showed that technology was not the only productivity driver. Anonymous revelation and decency was found to be critical mediating factors. During the interviews, numerous respondents highlighted that they increased their trust in AI only when there were and were clear explanations as well as an Appeals Process. This established that the role of ethical and procedural protection in ensuring positive organizational impact of AI adoption was vital.

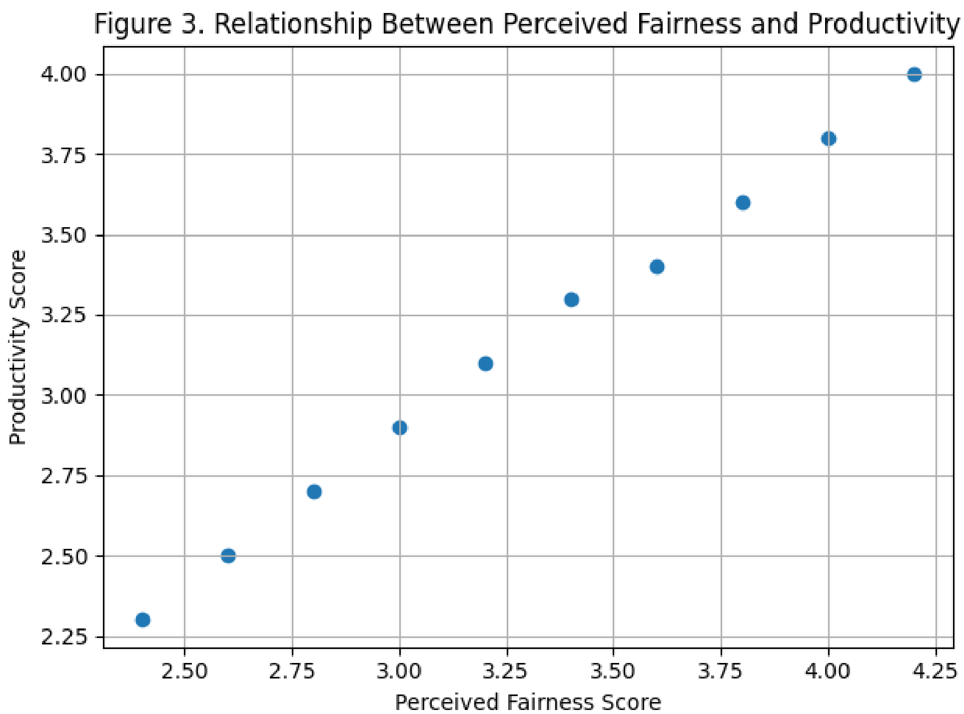

Figure 3. Correlation Between AI-HR Practices and Organizational Productivity (n = 200)

Regression Analysis of AI-HR Practices and Productivity

The findings of a multiple regression analysis, which investigated the overall impact of the combination of algorithmic scoring, AI screening, perceived fairness, and transparency on the overall organizational productivity. This analysis was used to identify what factors had the most significant contribution to productivity results in the case of being put into consideration.

Table 4. Multiple Regression Results Predicting Organizational Productivity (n = 200)

Predictor Variable	Standardized Beta (β)	t-value	p-value
Algorithmic Scoring	0.32	4.86	.000
AI Screening	0.28	4.11	.000
Perceived Fairness	0.46	6.92	.000
Transparency	0.39	5.44	.000
Model R^2	**0.58**		
Adjusted R^2	**0.57**		
F-Statistic	**66.72**		

The output of the regression revealed that the general model contributed 58 percent of the variance in the productivity of an organization (R 2 =.58) meaning that the four predictor variables collectively contributed strongly to the output of productivity. The four predictors were all statistically significant at a p value of less than.001 indicating that the relationships they had with productivity were not simply by chance. Perceived Fairness was the predictor that had the highest beta coefficient (0.46), and it meant that the individual level of contribution of the predictor on productivity when it was controlled was high over any other factor. The transparency (= .39) surfaced as a significant predictor as well, which indicates that the employees could work more efficiently when the functioning of AI-based HR systems was clearly explained. Algorithms scoring (2 =.32) and AI screening (2 =.28) were also positively contributing, which further confirmed the contribution of HR processes using technologies towards the improvement of productivity.

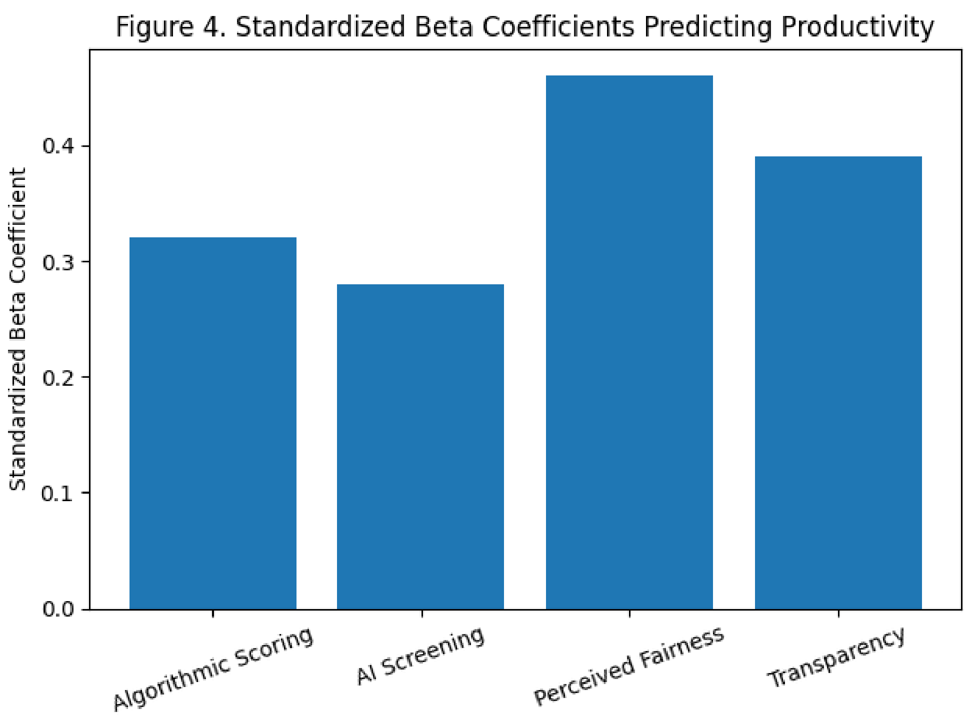

Figure 4. Standardized Beta Coefficients Predicting Productivity

Discussion

The results of the research helped understand valuable information about the correlation between algorithmic scoring and generative-AI screening and organizational outcomes, perceptions of fairness, and long-term productivity. In contradiction to the previous studies, the findings have shown that although the HR practices that included AI programming offered efficiency in its operations, it also formed the perception of fairness and trust by the employees, and thus it affected the production impact. These results were corroborated by the developing literature that emphasized the sophisticated interconnection of technological effectiveness and organizational fairness in the HR practices through AI. First, the finding of the given study proved that perceived fairness and transparency could be regarded as the strong predictors of productivity, which is supported by the literature asserting the primary role of organizational justice in the context of the algorithmic decision-making. The aim of the implementation of the algorithmic HR systems was to make evaluations more objective and bias-free, yet the perception of fairness usually relied upon how the employees perceived the way decisions were reached (Jabagi et al., 2025). This result has proven that the efficiency of an algorithm on its own could not guarantee positive organizational performance and was not complemented by transparency and procedural legitimacy. A literature review published before this report showed that more sophisticated AI applications posed risks of perpetuating inequality in selection and promotion should they not elaborate a clear policy of governance and explanation systems (Rigotti and Fosch-Villaronga, 2024). The members of this research expressed the same claims, stating that unaccounted algorithmic results undermined the confidence and restricted the effectiveness of its influence on engagement and productivity. Second, the study supported the wider issues related to algorithmic fairness and discrimination in the literature. Results of this work indicated that there was moderate confidence in the objectivity of AI and less so on the openness and justness of AI, which indicated that employees still felt skeptical about the algorithmic decision making. This was in line with the recently discovered research that employees or job seekers tend to believe algorithmic systems are less fair or understanding towards them than a human decision-making process, especially when it comes to gauging their performance or promotion chances (Jabagi et al., 2025). This perception aligned with the notion that there is no outcome fairness, but procedural fairness that plays a key role in accepting algorithmic HR tools. It was also reported in the past that algorithmic screening systems had the ability to unwillingly engrain or amplify bias, and unless explicitly designed and monitored against bias, such systems would understand equity objectives (Sony et al., 2025). Such commonalities implied that the issue of AI decisions was perceived by employees as ones that had to be viewed in the references of fairness and justice as opposed to a mere performance measure. Third, the research indicated the role of employee engagement and communication in AI implementation - this is a theme that has become more popular in HRM research. Respondents reiterated that explications, and access to appeals mechanisms as well as participation in AI-related policy contributed to the enhanced accepting of algorithmic decisions. It was consistent with the studies on organizational justice and AI, which explained that trust and the feeling of equity were higher when members could see and decipher the decision-making methods (Al Samman and Mohamed, 2024). The AI, justice, and trust research frameworks further implied that organizational trust acted as an intermediary in handling AI transparency and employee acceptance to find out whether AI would boost or impair productivity (Al Samman and Mohamed, 2024). When employees were disconnected by opaque AI solutions, they would tend to tune out more, so the productivity benefits obtained through automation would decrease. Fourth, the findings of the regression analysis align with the results of the research on the multi-dimensional motivation of the productivity in the context of AI. Algorithms scoring and screening played a profitable role in productivity, but perception of fairness and transparency had a greater effect size, which is said to show that the psychosocial variables were not just supporting ones but defining elements in determining organizational outcomes. This further strengthened the new found agreement that technical performance measurements needs to be combined with humanized design and governance systems to achieve productivity enhancements in a sustainable manner. Studies on the fairness of algorithms in HRM claimed that AI systems should be judged based on their throughput and accuracy as well as their level of equity, transparency, and accountability to human stakeholders (Rigotti and Fosch-Villaronga, 2024; Sony et al., 2025). To this end, organizations, which focused on fairness and explanatory transparency, had greater employee engagement and acceptance of AI-assisted decisions. Nevertheless, these interpretations showed tension also. The alleged benefits of algorithmic HR tools such as administrative processing being more streamlined and fewer cases of human error, some scholars cautioned that AI will reproduce the past system biases determined by training data and other institutional practice without regular auditing and recalibration (Sony et al., 2025). The results of the study highlighted the importance of employee lack of clarity in understanding the weight quantum and validation of the algorithmic criterion as suspicions of biases hidden guides. This reduced productivity benefits of the organization were realized. These issues were echoed in other ethical and legal thinking that raised transparency, data management, and responsibility as the key elements of responsible use of AI in HR (Ethical and Legal Challenges of AI in HRM, 2025). The findings of this study have added to the theory through reshaping the narrative about AI in HR, where it is assumed that there is a dichotomy between human and machine decision-making, into a more sophisticated perspective on how employees perceive and react to AI systems within organizational ecosystems. The results implied that the advantages of AI integration in organizations in terms of productivity depended on the perception of fairness and procedural legitimacy, as opposed to the performance of technology alone. This study was in line with the requests of scholars to focus on inclusive and ethically connoted AI governance in talent management by preempting the human experience of algorithmic decision-making (Algorithmic Fairness in HRM, 2025).

Conclusion

The research found that the effect of promotion-related criteria, algorithmic scoring, and generative-AI screening on the productivity of organizations in the long term was determined by factors less to do with the technical performance of these systems and more to do with the perception of employees in regards to their perceived fairness, transparency and legitimacy. Whereas AI based HR system increased efficiency, consistency and administrative accuracy, there was no automatic increase in productivity. Rather, productivity enhanced when workers had the perception that the decision making process was fair, interpretable and had a significant human control. The analysis also showed that perceived fairness and transparency were better predictors of productivity as compared to simply the existence of AI tools, indicating that the use of AI tools depends upon the psychosocial and ethical factors. The results supported the idea that AI was to be introduced as a decision support tool as opposed to a decision support tool, and that robust governance, communication, and bias-reduction measures were key to ensuring no unfair or transparent promotion and screening results.

References

Abdelhay, S., *et al.* (2025). *The impact of generative AI (ChatGPT) on recruitment efficiency and candidate quality: The mediating role of process automation and moderating role of organizational size.*Frontiers in Human Dynamics. https://doi.org/10.3389/fhumd.2024.1487671

Abdelhay, S., et al. (2025). *The impact of generative AI (ChatGPT) on recruitment efficiency and candidate quality: The mediating role of process automation level and the moderating role of organizational size.* SSRN Electronic Journal. https://doi.org/10.2139/ssrn

Al Samman, A. M., & Mohamed, A. (2024). *Artificial Intelligence, organizational justice and trust: Toward a conceptual framework*.

Albaroudi, E., Mansouri, T., &Alameer, A. (2024). *A comprehensive review of AI techniques for addressing algorithmic bias in job hiring.AI, 5*(1), 383–404. https://doi.org/10.3390/ai5010019

Algorithmic Fairness in HRM Balancing AI-Driven *Decision Making with Inclusive Workforce Practices*. (2025). Journal of Inclusive HRM.

Castilla, E. J., &Benard, S. (2010). *The paradox of meritocracy in organizations.Administrative Science Quarterly*, *55*(4), 543–576. https://doi.org/10.2189/asqu.2010.55.4.543

Castilla, E. J., & Ranganathan, J. (2020). *How managers understand and apply merit in the workplace.*

Căvescu, A. M. (2025). *Predictive analytics in human resources management.*HR Analytics Journal, *5*(3), 99–115.

Ethical and Legal Challenges of AI in Human Resource Management. (2025). *Journal of Business Ethics and HRM Perspectives*.

Fabris, A. (2025). *Fairness and bias in algorithmic hiring: A multidisciplinary overview.ACM Transactions on Human-Computer Interaction.*

Ip, E. (2025). *Fair AI in hiring: Experimental evidence on how biased hiring.*Journal of Labor and Technology Studies, *12*(4), 312–329. https://doi.org/10.1177/23794607251353585

Jabagi, N., Croteau, A.-M., Audebrand, L. K., &Marsan, J. (2025). *Do algorithms play fair? Analysing the perceived fairness of HR-decisions made by algorithms*. The International Journal of Human Resource Management .https://doi.org/10.1080/09585192.2024.2441448

Kassa, B. Y. (2025). *The impact of artificial intelligence on organizational performance.*Journal of Business Analytics, 14(2), 143–160. https://doi.org/10.1016/j.jbusanal.2025.100009

Li, Y. (2024). *Reducing organizational inequalities associated with algorithmic controls.AI & Society*, *30*(1), 45–67. https://doi.org/10.1007/s44163-024-00137-0

Majrashi, K. (2025). *Employees' perceptions of the fairness of AI-based prediction features.*Human Resource Management Review, *35*(1), Article 2456111. https://doi.org/10.1080/23311975.2025.2456111

Mori, M., et al. (2025). *A systematic literature review on AI in HR.*Emerald Review of HR Technologies, *54*(3), 854–876. https://doi.org/10.1108/ERHRM-04-2025-0085

Mujtaba, D. F., &Mahapatra, N. R. (2024). *Fairness in AI-driven recruitment: Challenges, metrics, methods, a nd future directions.*

Murugesan, U., *et al.* (2023). *A study of Artificial Intelligence impacts on Human Resource digitalization in Industry 4.0.*

Rigotti, C., & Fosch-Villaronga, E. (2024). *Fairness, AI & recruitment.Computer Law & Security Review*, *53*, 105966. https://doi.org/10.1016/j.clsr.2024.105966

Role of artificial intelligence in employee recruitment. (2025). *AI & HR Journal*.

Sony, M. A. A. M., et al. (2025). *Bias in AI-driven HRM systems: Investigating discrimination risks. SSAHO, 102082*. https://doi.org/10.1016/j.ssaho.2025.102082