

The Impact of AI-Enabled Performance Management on Employee Diversity Construction in Enterprises

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Abstract. In the current era of digital transformation, DEI (diversity, equity, and inclusion) is becoming the core goal of corporate human resources. More and more enterprises have realized that building a truly diverse, fair, and inclusive working environment has become a key driver for stimulating enterprise innovation and promoting business growth. However, in traditional manual performance assessment, many factors hinder the development of DEI. For example, in current enterprises, widespread problems such as subjective bias and stereotypes hinder the progress of diverse employees. This paper adopts the method of literature research and case analysis to explore the comprehensive impact of AI performance management on workforce diversity. The research found that AI can reduce human judgment bias, improve assessment fairness, and support employee diversity and development. However, it also has problems such as algorithmic discrimination, rigid assessment indicators, and improper implementation management. In response, this paper proposes improvement measures from the perspectives of algorithm optimization, improvement of the evaluation system, and personnel management, which can provide practical references for enterprises to implement the AI performance system and promote diverse and inclusive management.

Keywords: AI-enabled Performance Management, Employee Diversity, DEI, Algorithmic Fairness

1. Introduction

Diversity, Equity, and Inclusion (DEI) has become a strategic priority for enterprises worldwide. Amid this trend, performance management systems—the core mechanism through which employees are evaluated and developed—inevitably play a decisive role in shaping workforce diversity outcomes. However, in traditional performance assessment, the subjective evaluation of managers often dominates the performance assessment of employees, thus often leading to unfair phenomena such as treating older employees, female employees, and employees from different regions differently, making it difficult to protect the legitimate rights and interests of diverse groups and becoming a major obstacle for enterprises to implement DEI. The popularity of AI-driven performance management tools has sparked great optimism regarding the overcoming of human biases. By employing standardized algorithms, real-time data analysis, and quantifiable metrics, these systems are expected to replace subjective management judgments with objective data-driven

evaluations. However, existing research mainly focuses on the operational benefits of AI in human resource management, particularly cost reduction and efficiency improvement, but pays insufficient attention to the fairness impact brought about by this technological transformation. Currently, there are still few studies exploring whether and how AI performance management affects employee diversity building. Based on this, this article will successively analyze the positive values and practical limitations of AI performance management, and, in combination with the existing management models of enterprises, propose optimization paths.

2. The positive role of AI performance management in promoting employee diversity initiatives

2.1. Enhance the objectivity and fairness of performance evaluation

Traditional performance management is highly dependent on the subjective judgment of managers. Throughout the entire evaluation process, managers are consistently subject to systematic interference from two cognitive biases: the recency effect and the halo effect. The recency effect leads to overemphasis on employees' recent performance, which consequently penalizes groups with unstable work rhythms, such as older workers experiencing a gradual decline in energy levels and working mothers who need to balance work and family responsibilities. The halo effect, by contrast, allows a single favorable impression to dominate the overall evaluation score, inherently favoring candidates who fit managers' inherent "ideal employee" stereotype. This ultimately results in a disconnect between evaluation outcomes and employees' actual work performance, which not only undermines procedural justice but also reduces employees' sense of organizational belonging. In contrast, AI-enabled performance management relies on pre-set quantitative indicators and standardized algorithmic models, and conducts quantitative evaluation based on objective data. It shifts the evaluation basis from managers' subjective impressions to objectively recorded work data stored in the system, while eliminating demographic attributes such as gender and age from model inputs, which effectively reduces human subjective intervention and improves the fairness and objectivity of performance evaluation [1]. After Hanu, an Indian internet enterprise, launched the PeopleStrong AI-powered OKR performance system, internal corporate data show that within only one year, the gap in performance scores between grassroots technical employees aged over 40 and their younger counterparts, as well as between female employees in operational positions and male employees in business positions, narrowed significantly. The evaluation discrepancy caused by manual scoring decreased by more than 60%, laying a solid foundation for the enterprise to advance employee diversity and workplace equity initiatives [2].

2.2. Reduce the gap in assessment among different groups

Traditional performance evaluations often involve varying assessment standards across groups. Employees with similar capabilities but from different backgrounds may face evaluation disparities. Over time, this can lead to internal conflicts and hinder the formation of inclusive teams. For instance, in traditional performance evaluations, female employees are often underestimated for their "interpersonal skills" and other non-business factors, while older employees are questioned about their learning ability and adaptability. Remote employees are often marginalized due to communication difficulties. These issues stem from the inherent and unconscious biases present in the decision-making process of managers. However, AI performance tools employ uniform and non-discriminatory assessment standards, which can eliminate non-task-related information such as

gender, age, and location, focusing on work outcomes and core competencies, thereby reducing unfair biases across different groups within the same evaluation system [3]. Furthermore, some studies have suggested that when employees receive feedback and evaluations from an "objective source" such as AI, minority group employees are less likely to attribute negative evaluations to discrimination, thereby mitigating the negative impact of "attribution ambiguity" on learning motivation and career development [4].

2.3. Reduce the burden on the HR department and enhance the execution capability of the DEI strategy

In the daily work of HR, repetitive tasks such as data statistics, performance report generation, and monthly preliminary evaluations have long consumed a significant amount of HR's staff's time and energy, making it difficult for the HR team to handle diverse core tasks such as female talent cultivation, career planning for older employees, and cross-cultural team integration. AI automation can effectively handle all routine transactional assessment tasks, freeing HR from cumbersome administrative tasks, and significantly reducing time spent on administration, and enabling the HR team to shift their focus to DEI-specific initiatives, thus truly implementing a long-term development mechanism for diverse talents.

3. The existing problems restricting the diversified development through AI performance management

3.1. The historical biases in the training data and algorithm aversion

The evaluation logic of AI models is entirely derived from training on historical assessment data from the enterprise. If discriminatory evaluations targeting disadvantaged groups are still present in the past performance records, the algorithm will also learn and replicate the unfair standards, resulting in imperceptible algorithmic biases [5]. The Amazon AI recruitment tool is a prime example of this risk: The system was trained based on resume data dominated by men over the past decade, and it learned to lower the scores of resumes containing female-related words. Eventually, it was halted in 2015 due to its inability to eliminate gender bias [6]. This case demonstrates that AI systems are not inherently neutral; their decision-making logic is deeply embedded in the social biases of the training data. More notably, the AI algorithm aversion phenomenon further amplifies the negative impact of algorithmic bias. AI algorithm aversion refers to the situation where, despite the algorithm performing more accurately or more fairly in certain tasks, people still tend to distrust the algorithm's decisions [7]. Research shows that the greater the decision-making power of AI, the lower the employee satisfaction - even if they believe the assessment process itself is fair, they may still be dissatisfied simply because "the decision was made by the AI" [8]. Algorithm bias and algorithm aversion often reinforce each other: the more obvious the bias, the stronger the aversion; the stronger the aversion, the less cooperation and constructive feedback employees provide to the system, and the weaker the foundation for system optimization becomes.

3.2. Excessive quantification of indicators leads to uniformity, while the absence of diversified indicators restricts multi-dimensional evaluation

Currently, most AI performance systems still center on traditional key performance indicators (KPIs), with quantifiable outputs such as sales volume, production output, and labor hours

dominating evaluation frameworks. There is a lack of assessment dimensions for non-quantifiable contributions, including creative output, teamwork, and humanistic services. As a result, diverse, multi-dimensional performance management remains superficial, making it difficult for talented individuals who excel in creativity, human-centered services, and cross-team collaboration to receive objective and positive evaluations. When enterprises rely entirely on AI-based scoring to screen talent, they risk losing these distinctive, diverse professionals—contradicting the original intent of building diversity, equity, and inclusion (DEI).

3.3. The emergence of the performance migration illusion

Performance migration illusion is a deep-seated cognitive trap that hinders the effective functioning of artificial intelligence-enabled performance management. It refers to the error that occurs when an AI system quantifies employee performance, incorrectly equating actual job performance with certain behaviors that have weak or no correlation with core work outputs—such as online activity duration and system click frequency, which serve as process indicators. As a result, the focus of performance evaluation is shifted from "real value creation" to "superficial behaviors that can be easily captured by machines". Management research has confirmed that in human-machine collaboration scenarios, managers may fall prey to the "performance migration illusion", incorrectly attributing performance contributed by machines to employees themselves. From the perspective of diversity promotion, the destructiveness of performance migration illusion lies in that it disguises itself as "technically neutral" and conceals the deviation of evaluation criteria: when older employees, employees with disabilities, or remote employees are rated as "low-performing" because their work styles do not conform to the behavior patterns preferred by algorithms, AI presents evaluation results under the pretext of "data-driven decision-making". Compared with bias in traditional evaluation, this injustice is far more difficult to identify and appeal against. Therefore, identifying and preventing performance migration illusion is a key link in ensuring the effectiveness of AI-enabled performance management and safeguarding the rights and interests of employees to fair evaluation in a diverse context [9].

4. Countermeasures for improving AI performance and enabling diversification from the perspective of human resources

In response to the multiple constraints identified in the previous section, the HR department should actively participate in the full lifecycle management of the AI performance system, optimizing across five dimensions: indicator design, algorithm auditing, employee communication, risk prevention, and institutional ethics. This will mitigate the negative impact of AI on employee diversity and development.

4.1. Establish a performance indicator system oriented towards diversity

Currently, AI performance systems generally center on traditional quantitative KPIs such as sales volume, output, and working hours, lacking evaluation dimensions for employees' diversity contributions. Therefore, HR should lead the reconfiguration of the overall indicator framework and add special assessment indicators for DEI such as cross-cultural collaboration outcomes, team inclusiveness building, and inclusive leadership. Decompose the company's DEI development goals layer by layer into performance standards for each position, converting diversity building from a slogan to quantifiable and traceable regular management content. At the same time, for diverse

talents who excel in creative output, people-oriented services, and cross-group coordination, establish independent evaluation channels or set special weighted indicators to fully identify their differentiated value and avoid the loss of such talents due to a single quantitative assessment logic.

4.2. Regularly conduct special audits of algorithm fairness

In response to the problem that AI may replicate inherent discrimination and unfairness against specific groups in historical assessment data [1], enterprises need to establish an internal or third-party algorithm auditing mechanism. This mechanism should regularly compare the performance scores of disadvantaged groups such as women, older individuals, employees with disabilities, and remote employees with those of the mainstream group. Once significant score deviations are detected, it should promptly correct model parameters and balance the training dataset [10]. At the same time, the mechanism should link the fairness audit with the accountability mechanism to avoid the audit becoming a formality without substantive rectification actions [1]. For groups such as women and middle-aged employees who are vulnerable to bias, the mechanism should conduct targeted audits to prevent algorithm replication of historical discriminatory evaluations.

4.3. Alleviate algorithm aversion and establish an employee participatory human-machine collaborative mechanism

The higher the decision-making authority of the AI system, the stronger employees' resistance. Even if the assessment process is objective and fair, employees will still be dissatisfied with the machine-dominated evaluation [8]. HR needs to define a clear role for the AI system, using the system output only as a performance reference, while leaving the final decision-making power over major personnel decisions—such as salary adjustments, promotions, and staff optimization—in the hands of managers. The enterprise needs to disclose the AI scoring logic, data sources, indicator weights, and performance appeal channels to all employees [6], and establish an employee feedback mechanism that invites representatives to participate in the system iteration research, thereby improving the review and appeal process and strengthening employees' recognition of the assessment system. Relevant research has confirmed that providing employees with feedback and appeal channels can significantly enhance the perception of procedural fairness and effectively reduce the negative feelings caused by algorithm aversion [7]. This AI-assisted, human backup model of collaboration, which balances assessment efficiency and human inclusiveness, is a performance management path suitable for diversity management.

4.4. Establish a performance migration review mechanism and supplement contextual human calibration

The performance migration illusion causes AI to overemphasize surface process indicators such as online duration and system clicks, confusing employees' surface behaviors with their true value creation, and resulting in implicit injustice [9]. To avoid this problem, HR needs to regularly conduct performance calibration. Managers should supplement contextual information not captured by AI, such as job difficulty, specific external constraints during the assessment period, and team collaboration contributions, and differentiate between algorithm-preferred behaviors and employees' true performance. For groups such as older, disabled, and remote employees with special working patterns, HR should specifically check whether the weights of algorithm behavior indicators are structurally underestimated; and regularly review cases of employees who receive extremely high or

extremely low scores from AI, verify whether the scoring logic is in line with actual work output, and promptly correct the evaluation bias caused by the illusion of performance migration, thereby ensuring the fair evaluation rights of diverse employees.

4.5. Improve internal AI performance management systems and DEI ethical norms

The enterprise needs to formulate unified AI human resources ethical guidelines, embedding anti-discrimination and fairness and inclusion requirements throughout the process of algorithm design, use, and iteration [10]. These guidelines are accompanied by three basic tasks: First, incorporate the promotion of team diversity into the performance assessment of managers; second, regularly conduct HR digitalization and basic algorithm training to enhance practitioners' ability to identify AI risks; third, establish a compliance review process for the AI performance system to uphold the fairness of the algorithm and prevent the tool from replicating historical workplace biases. Only by simultaneously implementing technological optimization and institutional constraints can the positive value of AI performance management tools be truly realized, and continuously support the long-term development of workforce diversity in the enterprise.

5. Conclusion

With the rapid popularization of AI performance management in enterprises, its dual impact on employee diversity building has gradually become a key research topic in both academia and industry. This study confirms that in the context of digital transformation, AI performance management has both positive enabling value and potential risk for enterprise diversity building. On the positive side, standardized algorithm assessment can weaken subjective cognitive biases such as the halo effect and recency effect of managers, remove irrelevant interfering factors such as gender, age, and region through unified quantitative indicators, and effectively narrow the performance score gap among different employee groups; at the same time, it automates the processing of report statistics and monthly preliminary reviews of routine work, freeing up the HR team's time and energy and enabling them to focus on core DEI work such as female talent cultivation, career planning for older employees, and cross-cultural team integration.

However, the inherent shortcomings of the algorithm continue to hinder the implementation of fair diversity evaluation: historical training data will replicate the long-standing implicit discrimination in the workplace, and a single KPI system based on sales volume and working hours is difficult to measure the soft contributions of employees in inclusive collaboration and team diversity building. In addition, performance migration illusion and the cognitive trap of algorithm aversion will compound and amplify the unfairness of the evaluation, deepen employees' resistance to machine-dominated assessment, and significantly weaken the actual effect of AI in enabling diversity management.

To balance assessment efficiency and fairness for diverse groups, the HR department needs to establish a full-process governance system: optimize comprehensive performance indicators covering diverse values, conduct regular audits of algorithm fairness, rely on manual reviews and performance sampling to avoid score distortion caused by superficial behavioral indicators; simultaneously, introduce enterprise AI ethics norms to leverage the technical advantages of the human-machine collaborative evaluation model, and create a fair and inclusive performance evaluation environment for diverse employees.

This study provides a theoretical analytical framework and practical approaches for enterprises to balance technical efficiency and DEI development goals in the digital context. As an exploratory

study, this paper adopts literature analysis and case induction as its primary research methods, and still lacks direct verification from empirical data. Future research can conduct questionnaire surveys or quasi-experimental studies across different industries to examine the differentiated impacts of AI-powered performance management on the fairness perception of different groups, and explore the dynamic relationship between algorithmic transparency and employee trust, so as to further improve the theoretical model of AI-enabled diversity management.

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