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EXAMINING BIAS IN AI-POWERED PERFORMANCE EVALUATION TOOLS AND MITIGATION STRATEGIES

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Abstract

This paper investigates professionals' perceptions on bias in AI powered performance evaluation tools and mitigation strategies. The research analyzed survey data collected from 260 respondents across multiple roles and industries to see if user roles relate to their concerns about bias and their views on the characteristics of AI tools. A statistical analysis further showed no significant association between bias concerns and primary role ($\chi^2(24)=11.2$, $p=0.987$), indicating that concerns are widespread throughout all positions. Nevertheless, there was a strong positive correlation in the level of concern that bias would be perpetuated by AI ($\beta=0.499$, $p<.001$, $R^2=0.381$), and the perceived importance of human oversight in curbing it. Generally, respondents perceived the bias potential of AI tools as moderate-to-high, had limited-to-moderate trust, and transparency was generally lacking while AI tools should be overseen by a human and specific training is overwhelmingly supported. The results show key ways to enhance fairness, clarity, and assurance in AI used for HR matters.

Keywords:

AI Bias, Performance Evaluation, Algorithmic Fairness, HR Technology, Mitigation Strategies

1. INTRODUCTION

Artificial Intelligence (AI) is quickly changing Human Resource Management (HRM), including advancement in efficiency, consistency, and data driven decision making [1], [2] especially in the processes of performance evaluation. Subrahmanyam [3] says AI powered tools take into consideration several different types of employee data; productivity metrics, and qualitative employee feedback, in an attempt to objectively and completely gauge an employee's performance. The use of these technologies can then minimise subjective evaluation as it is in traditional human evaluation [4].

But this integration of the technological is fraught with ethical challenges, first the risk of putting and reinforcing unjust biases [5], [6]. An algorithm trained on historical correlated data related to past societal or organizational discrimination on gender, race, age, or some other factor [7], [8] may inadvertently redress that same discrimination. Some of these biased outcomes can negatively impact important decisions such as who receives promotions what compensation packages and career development, which can lead to employees losing trust of the company and legal consequences [9], [10].

With this much on the line, it is essential to understand how professionals who use, manage, or are evaluated by these AI systems approach them. This paper explores stakeholders' perception of bias potential in AI evaluation tools, perceived effectiveness of existing mitigation strategies used in these tools, and overall trust in these systems. Finally, it describes how concerns of bias are correlated with the demand for safeguards such as human oversight, which are crucial to determine the viability of developing and implementing fairer and more trustworthy AI for performance management [11].

2. PROBLEM STATEMENT

With the growing adoption of AI in performance evaluation, there is now a dual challenge of taking advantage of the technological potential in terms of efficiency, at the same time as minimizing the risks of bias, and maintaining fairness. Firms do not have enough empirical knowledge about how different stakeholders (HR, managers, employees) understand the bias of these tools and how current mitigation efforts reduce it.

It is critical to determine if people perceive the problem differently depending on their roles, to quantify the effect of concern about bias on demand for safeguards such as human oversight, and to measure general levels of trust and confidence. Without this understanding, organizations risk implementing AI solutions that erode employee trust, perpetuate discrimination, and fail to deliver genuinely fair evaluations.

3. LITERATURE REVIEWS

AI is applied in the performance evaluation that represents a significant evolution in comparison to the traditional methods of assessment that are often subjective and are most often dependent on past experience. The motivation behind this shift is to gain more objective, effortless and meaningful methods to manage and grow the workforce talent [2].

3.1 EMERGENCE OF AI IN PERFORMANCE EVALUATION

A range of employee data points is being put into AI systems to analyze. It might also mean quantitative data, such as sales figures or project completion percentage, or qualitative data: sentiment analysis on written feedback or peer review [1]. Predicting future performance or finding out probable flight risks for predictive analytics, and also ranking employees on the basis of predefined criteria is done with automated scoring systems [3].

Even advanced tools often analyze the communication pattern or interaction in a video with the intention to measure competencies or engagement level (cf. survey Q6). The aim is to free the hands of managers from the repetitive tasks of unnecessary data collection, and to empower managers rather than burden them with data while enhancing the level of standardization in the evaluation of professors [12].

3.2 CHALLENGE OF ALGORITHMIC BIAS

Yet as an objective tool, AI tools still suffer from bias. The first one is the question of data bias—the algorithms trained on historical datasets learn the historical discrimination patterns

inherent in this data [7], [5]. If AI previously evaluated gender or racial disparities, the AI could learn and proselytize the same.

Design choices, i.e., feature selection or the use of proxy variables, which correlate with protected characteristics, can cause Algorithmic Bias [8]. Additionally, Interaction Bias also occurs over time, if user feedback reenforces biases already in the system. They can be subtle or quite impactful on fairness across demographics [13], [10].

3.3 ETHICAL IMPERATIVES AND ORGANIZATIONAL IMPACT

Algorithmic bias has profound ethical questions in relation to fairness, equity and integrity of HR processes [6], [13]. This can create unfair decisions made unfairly based on careers, the danger of loss of employee trust and spirit (cf Q15 survey) way as well as the organizations' intensifying exposure to valid legal challenges based on discrimination [9].

And because of this black box nature of many AI algorithms, which are opaque in their decision making, accountability in challenging potentially unfair outcomes is compromised [12], [14]. To tackle these ethical risks for AI deployment, they need to be committed to the Fairness, Accountability, and Transparency (FAT) principles.

3.4 MITIGATION STRATEGIES AND HUMAN OVERSIGHT

In response to these challenges, there have been many mitigation strategies in practice. Some of the approaches to address this problem are conducting algorithmic audits to detect bias by rigorous algorithms, having diverse training datasets to curation and fairness constraints consideration in the development of the model, as well as to enhance the explainability of AI output [8], [11].

However, technology is not usually enough by itself. Finally, a human manager is involved in robust human oversight, reviewing AI generated insights through calibration meetings, and preserving the final decision making authority (see survey Q12).

Further, AI literacy, bias detection and ethical usage training for HR professionals and managers is necessary for the safe usage (cf. survey Q14; [11]). Such strategies are still an ongoing focus of development and application for their effectiveness [15].

3.5 RESEARCH GAP

While literature explores AI bias mitigation strategies [8] and ethical frameworks broadly [6], [9], specific empirical gaps remain relevant to this study. Quantitative research assessing how perceptions of bias potential specifically differ across distinct professional roles (HR, managers, employees) involved in or subject to AI-powered *performance evaluations* is limited.

Furthermore, although human oversight is recommended as a critical safeguard [11], the predictive relationship between practitioners' *level of concern* about AI perpetuating bias and their *demand* for significant human intervention requires robust empirical validation using stakeholder perspectives. This study directly addresses these gaps.

4. RESEARCH DESIGN

4.1 RESEARCH APPROACH

This study utilized a quantitative, cross-sectional survey design to examine perceptions and attitudes regarding bias in AI-powered performance evaluation tools and associated mitigation strategies. The approach allowed for statistical analysis of relationships between demographic/role variables and attitudinal measures.

4.2 RESEARCH OBJECTIVES

The research was guided by the following objectives:

- To examine if the primary role in performance management is associated with the perceived potential for unfair bias in AI evaluation tools. (analyzed)
  - *Rationale:* To understand if different stakeholder groups (HR, managers, employees, etc.) hold varying levels of concern about bias potential.
- To determine if the level of concern about AI perpetuating bias predicts the perceived importance of significant human oversight in AI-assisted performance evaluations (analyzed)
  - *Rationale:* To quantify the link between recognizing the risk and valuing human intervention as a safeguard.
- To investigate the relationship between familiarity with AI tools and the level of trust placed in their fairness for performance evaluation. (Additional Objective)
  - *Rationale:* To explore whether greater familiarity with AI concepts translates into higher or lower trust in their fairness within this specific application.

4.3 SAMPLING

Data was gathered from 260 respondents using convenience and snowball sampling, primarily distributed via online channels. The sample included individuals in various roles related to performance management (HR Professionals: 30.0%, People Managers: 27.7%, Employees: 24.2%, IT Staff: 8.5%, Executives: 5.8%, Consultants: 3.8%), across diverse industries (led by Technology/IT: 29.2%) and experience levels (centered around 2-10 years).

4.4 DATA COLLECTION INSTRUMENT

A structured online questionnaire with 16 closed-ended questions was administered. The questionnaire captured:

- Demographics/Role: Primary Role, Industry, Years of Experience.
- AI Familiarity & Usage: Familiarity level, Organizational usage, Types of AI functions, HR process application.
- Perceptions & Attitudes: Potential for bias, Trust, Concern, Transparency, Importance of oversight, Mitigation effectiveness, Training cruciality, Morale impact, Confidence in mitigation.

4.5 DATA ANALYSIS TECHNIQUES

Data analysis was conducted using Jamovi statistical software (Version based on output format, assumed latest stable). Key techniques employed:

- Descriptive Statistics: Frequencies and percentages for all variables to summarize sample characteristics and overall response patterns.
- Chi-Square Test of Independence: Used for Objective 1 to test the association between Primary Role (Nominal) and Perceived Bias Potential (Ordinal).
- Linear Regression: Used for Objective 2 to assess the predictive relationship between Concern about Bias (Ordinal treated as Continuous) and Importance of Human Oversight (Ordinal treated as Continuous).
- (For Objective 3): Spearman's Rank Corelation would be used to measure the monotonic relationship between AI Familiarity and Trust in AI Fairness.
- The significance level (alpha) was set at 0.05 for all inferential tests.

4.6 ETHICAL CONSIDERATIONS

Participants were informed about the study's purpose, assured of anonymity and data confidentiality, and participation was entirely voluntary. No sensitive personal identifiable information beyond the role/demographic context was collected.

5. DATA ANALYSIS AND FINDINGS

5.1 DATA ANALYSIS - OBJECTIVE 1

To examine if the primary role in performance management is associated with the perceived potential for unfair bias in AI evaluation tools.

5.1.1 Hypotheses:

- Null Hypothesis (H0): There is no significant association between the primary role in performance management and the perceived potential for unfair bias in AI-powered performance evaluation tools.
- Alternative Hypothesis (H1): There is a significant association between the primary role in performance management and the perceived potential for unfair bias in AI-powered performance evaluation tools.

5.1.2 Variables:

1) Independent Variable: Primary Role (Categorical)
   a) *Source:* "What is your primary role in relation to performance management?"
   b) *Levels:* HR Professional / Manager, People Manager / Team Lead (Non-HR), Individual Contributor / Employee, IT / Technical Staff supporting HR systems, Executive Leadership, Consultant / External Advisor.

Table.1. Primary role by perceived potential for bias

Primary Role		High Potential	Moderate Potential	Very High Potential	Low Potential	Very Low Potential	Total
People Manager / Team Lead (Non-HR) (1)	Observed	1	0	0	0	0	1
	Expected	0.30	0.35	0.15	0.13	0.07	
HR Professional / Manager	Observed	24	31	14	11	8	88
	Expected	26.06	30.80	13.20	11.51	6.43	
Individual Contributor / Employee	Observed	21	21	8	6	3	59
	Expected	17.47	20.65	8.85	7.72	4.31	
People Manager / Team Lead (Non-HR) (2)	Observed	16	21	8	8	5	58
	Expected	17.18	20.30	8.70	7.59	4.24	
IT / Technical Staff supporting HR	Observed	10	8	4	4	1	27
	Expected	8.00	9.45	4.05	3.53	1.97	
Executive Leadership	Observed	3	6	1	3	1	14
	Expected	4.15	4.90	2.10	1.83	1.02	
Consultant / External Advisor	Observed	2	4	4	2	1	13
	Expected	3.85	4.55	1.95	1.70	0.95	
Total	Observed	77	91	39	34	19	260
	Expected	77.00	91.00	39.00	34.00	19.00	

2) Dependent Variable: Perceived Potential for Bias (Ordinal, treated as Categorical for Chi-Square)
   a) *Source:* "In your opinion, what is the general potential for unfair bias"
   b) *Levels:* Very High Potential, High Potential, Moderate Potential, Low Potential, Very Low Potential.

5.1.3 Statistical Test: Chi-Square Test of Independence:

The Table.1 for Primary role by perceived potential for bias Counts (Observed and Expected) and Row Percentages.

Table.2. χ^2 Tests

Test	Value	df	p
χ^2	11.2	24	0.987
χ^2 continuity correction	11.2	24	0.987
N	260		

Table.3. Nominal Measures

Measure	Value
Contingency coefficient	0.203
Phi-coefficient	NaN
Cramér's V	0.104

5.2 INTERPRETATION

A Chi-Square test examined the association between the respondent's primary role (e.g., HR, Manager, Employee) and their perceived potential for unfair bias in AI evaluation tools. The result was not statistically significant ($\chi^2(24) = 11.2$, $p = 0.987$). As the p-value is greater than 0.05, we fail to reject the null hypothesis (H0). This indicates no significant evidence in this sample that an individual's primary role in performance management is associated with their perception of the potential for bias in these AI tools. The very small effect size (Cramér's V = 0.104) further supports the lack of a meaningful relationship.

5.3 DATA ANALYSIS - OBJECTIVE 2

To determine if the level of concern about AI perpetuating bias predicts the perceived importance of significant human oversight in AI-assisted performance evaluations.

5.3.1 Hypotheses:

- Null Hypothesis (H0): The level of concern about AI perpetuating bias does not significantly predict the perceived importance of significant human oversight ($\beta = 0$).
- Alternative Hypothesis (H1): The level of concern about AI perpetuating bias significantly predicts the perceived importance of significant human oversight ($\beta \neq 0$).

5.3.2 Variables:

- Independent Variable (Predictor): Concern about Bias (Ordinal, treated as Numeric/Continuous)
- Source: "How concerned are you about AI tools potentially perpetuating or amplifying existing societal biases"
- Levels (to be recoded numerically): Not Concerned At All=1, Slightly Concerned=2, Moderately Concerned=3, Very Concerned=4, Extremely Concerned=5
- Dependent Variable (Outcome): Importance of Human Oversight (Ordinal, treated as Numeric/Continuous)
- Source: "In performance evaluation processes involving AI tools, how important is having significant human oversight"
- Levels (to be recoded numerically): Not Necessary=1, Slightly Important=2, Moderately Important=3, Very Important=4, Absolutely Essential=5

Statistical Test: Linear Regression

Table.4. Model Fit Measures

Model	R	R^2	Overall Model Test: F	Overall Model Test: df1	Overall Model Test: df2	Overall Model Test: p
1	0.618	0.381	159	1	258	<.001

Table.5. Omnibus ANOVA Test

Source	Sum of Squares	df	Mean Square	F	p
Concern about Bias	88.8	1	88.808	159	<.001
Residuals	144.0	258	0.558		

Note. Type 3 sum of squares

Table.6. Model Coefficients - Importance of Human Oversight

Predictor	Estimate	SE	95% Confidence Interval: Lower	95% Confidence Interval: Upper	t	p
Intercept	2.324	0.1427	2.043	2.605	16.3	<.001
Concern about Bias	0.499	0.0395	0.421	0.577	12.6	<.001

Table.7. Normality Test (Shapiro-Wilk)

	Statistic	p
Residuals	0.916	<.001

Linear regression assessed if the level of concern about AI perpetuating bias predicts the perceived importance of significant human oversight. The overall model was significant ($F(1, 258) = 159$, $p < .001$). Concern about bias was found to be a strong, statistically significant predictor of the perceived importance of human oversight ($\beta = 0.499$, $p < .001$). Therefore, the null hypothesis is rejected. This positive relationship indicates that individuals with higher concern about AI bias perceive human oversight as significantly more important. Concern about bias explains 38.1% of the variance in perceived oversight importance ($R^2 = 0.381$). Note: The assumption of normally distributed residuals was violated (Shapiro-Wilk $p < .001$), warranting caution in interpretation.

Table.8. Descriptive Statistics for AI Bias in Performance Evaluation

Question	Most Common Response	%	Second Most Common	%	Key Distribution Pattern
1. Primary Role	HR Professional / Manager	30.0%	People Manager / Team Lead	27.7%	Dominated by HR and Managers
2. Industry	Technology / IT Services	29.2%	Finance / Banking / Insurance	17.3%	Tech leads, Finance second, diverse overall
3. Years Experience	6-10 years	30.4%	2-5 years	25.8%	Centered around mid-career (2-10 years)
4. AI Familiarity	Somewhat Familiar	35.4%	Slightly Familiar	24.6%	Mostly basic/slight familiarity
5. AI Tool Usage	Yes, for specific tasks/pilots	33.5%	No	26.2%	Mixed usage, pilots/limited use most common
6. AI Functionality used	Automated analysis of written feedback	23.8%	Analysis of productivity metrics	20.8%	Feedback & productivity analysis lead
7. HR Process Use*	Annual/Semi-annual performance reviews	26.5%	Identifying high-potential employees	17.7%	Core reviews & talent ID primary uses
8. Potential for Bias	High Potential	31.5%	Moderate Potential	29.2%	Skewed towards Moderate/High potential
9. Trust in AI Fairness	Moderate Trust	37.7%	Limited Trust	30.0%	Centered on Moderate/Limited trust
10. Concern about Bias	Very Concerned	31.5%	Moderately Concerned	26.5%	Skewed towards Moderate/High concern
11. Transparency	Neutral / Varies Greatly	32.3%	Somewhat Opaque	28.1%	Generally perceived as Neutral to Opaque
12.Importance Human Oversight	Absolutely Essential	41.2%	Very Important	33.1%	Overwhelmingly seen as Important/Essential
13.Effectiveness Mitigation	Slightly Effective	31.5%	Moderately Effective	24.2%	Perceived as Slightly/Moderately effective at best
14. Cruciality Training	Critically Needed	35.8%	Highly Necessary	33.5%	Overwhelmingly seen as Necessary/Critical
15. Impact on Morale/Trust	Slightly Negative Impact	32.3%	Neutral / No Significant Impact	27.7%	Leaning towards Neutral/Negative impact
16. Confidence Mitigating Bias	Neutral / Uncertain	35.0%	Slightly Confident	26.2%	Centered on Uncertainty/Slight confidence

5.4 DESCRIPTIVE STATISTICS

Refer Table.8 for Descriptive statistics

5.5 FINDINGS

Based on the analysis of 260 survey responses regarding AI bias in performance evaluation:

- Role vs. Bias Perception (No Link): There is no statistically significant association between an individual's primary role (e.g., HR, Manager, Employee) and their perception of the potential for bias in AI evaluation tools ($\chi^2(24) = 11.2$, $p = 0.987$), suggesting bias concerns are widespread across roles.
- Concern Drives Need for Oversight: Concern about AI perpetuating bias is a strong and statistically significant positive predictor of the perceived importance of human oversight ($\beta = 0.499$, $p < .001$), explaining 38.1% of the variance ($R^2 = 0.381$).
- High Perception of Bias Potential: A majority of respondents perceive AI tools as having moderate (29.2%) to high (31.5%) potential for unfair bias, indicating prevalent skepticism.
- Limited Trust in AI Fairness: Trust in the fairness of AI-generated evaluations is generally low, centering around moderate (37.7%) and limited (30.0%) trust levels.
- Lack of Perceived Transparency: AI tool transparency is viewed poorly, with responses concentrated around neutral/variable (32.3%) and somewhat opaque (28.1%), suggesting difficulty in understanding how decisions are made.
- Overwhelming Demand for Human Oversight: There is a strong consensus on the need for human involvement, with 74.3% deeming significant human oversight "Absolutely Essential" (41.2%) or "Very Important" (33.1%).
- Low Confidence in Mitigation: Current strategies to mitigate AI bias are perceived as only slightly effective (31.5%) or moderately effective (24.2%) at best, with substantial doubt

about their efficacy (37.7% rated Not Effective/Ineffective/Unsure).

- Critical Need for Training: An overwhelming majority believe specific training on identifying and addressing AI bias is crucial, rating it "Critically Needed" (35.8%) or "Highly Necessary" (33.5%).

6. CONCLUSION AND SUGGESTIONS

6.1 CONCLUSION

This study reveals significant concerns surrounding the use of AI in performance evaluations. While perceptions of bias potential do not significantly differ based on professional roles (χ^2=11.2, p=0.987), indicating widespread apprehension, there is a strong consensus on the need for safeguards. Notably, higher concern about AI perpetuating bias strongly predicts a greater perceived importance of human oversight (β=0.499, p<.001, R^2=0.381). Respondents generally distrust the fairness of AI evaluations, view the tools as lacking transparency, perceive current mitigation strategies as inadequate, and overwhelmingly support mandatory human oversight and specialized training. These findings underscore a critical gap between the deployment of AI HR tools and the establishment of trust and confidence among stakeholders.

6.2 SUGGESTIONS

- Mandate Human Oversight: Implement clear protocols requiring significant human review, judgment, and final decision-making authority in all AI-assisted performance evaluations.
- Enhance Transparency: Prioritize the use or development of AI tools with greater explainability ("glass box" vs. "black box") and communicate clearly how they function.
- Develop & Validate Mitigation: Invest in robust bias detection audits and mitigation strategies (e.g., diverse data, fairness checks) and transparently validate their effectiveness.
- Implement Comprehensive Training: Provide mandatory training for HR, managers, and employees on AI literacy, potential biases, ethical implications, and how to interpret/challenge AI outputs.
- Establish Clear Governance: Create clear ethical guidelines and governance frameworks for the use of AI in performance management within the organization.
- Monitor Employee Trust: Regularly gauge employee morale and trust related to AI evaluation tools and adjust practices accordingly.
- Focus on Augmentation, Not Replacement: Position AI tools as decision-support systems that augment human judgment rather than replacing it.

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