

AI-Driven Performance Appraisal in India: A Socio-Technical Analysis of Efficiency, Bias, and Employee Trust

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India has emerged as one of the fastest adopters of AI-driven performance appraisal systems; nonetheless, little empirical data exists on how they can be applied within hierarchical-based, linguistically diverse, and culturally embedded organisational settings. The gap is especially problematic because algorithmic decision-making is becoming more and more influential on employee assessment and career advancement.

The proposed study is based on a convergent mixed-method design to address the issue of adoption, effectiveness, and ethical implications of AI-based appraisal systems among Indian organisations. Structural Equation Modelling (SEM) was used to analyse quantitative data collected from 312 HR professionals and employees in five fields, which include IT/ITES, manufacturing, banking, e-commerce, and pharmaceuticals, and thematic analysis was applied to the qualitative data collected on six organisational case studies.

The results show that AI-based appraisal systems can lead to better operational performance, with the time spent on the evaluation cycle being decreased by 43 percent and the consistency of cross-location ratings also being elevated. Moreover, the regulatory system in India is still more underdeveloped compared to international ones, especially in matters of transparency, explainability, and accountability of algorithmic decision-making. This paper presents one of the first large-scale empirical analyses of algorithmic bias in AI-enabled HR systems in an emerging economy, which offers both theoretical progress and practical information on how an AI-based performance management practice can be designed to be transparent, fair, and context-sensitive.

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Introduction

Artificial Intelligence (AI) is quickly transforming the manner in which organisations make decisions, especially in Human Resource Management (HRM), whereby algorithmic systems are increasingly used in order to streamline the performance evaluation process. The recent estimates provided by Statista (2025) suggest that by 2026, the global AI market will reach over 300 billion dollars, and HR analytics and workforce automation will become the primary areas of application. In HR functions, AI

adoption is accelerating, with over 58% of HR leaders reporting improved decision-making and automation reducing evaluation time significantly. To this end, a Gallup (2024) report shows that almost 75% of companies worldwide are exploring or already applying AI to at least one HR process, suggesting a paradigm shift in favour of data-driven workforce management. Recent Gallup (353-369) findings indicate that approximately 45% of employees use AI in workplace contexts, while only 10–12% engage with AI daily, reflecting uneven but rapidly growing adoption.

How Much Are U.S. Workers Using AI?

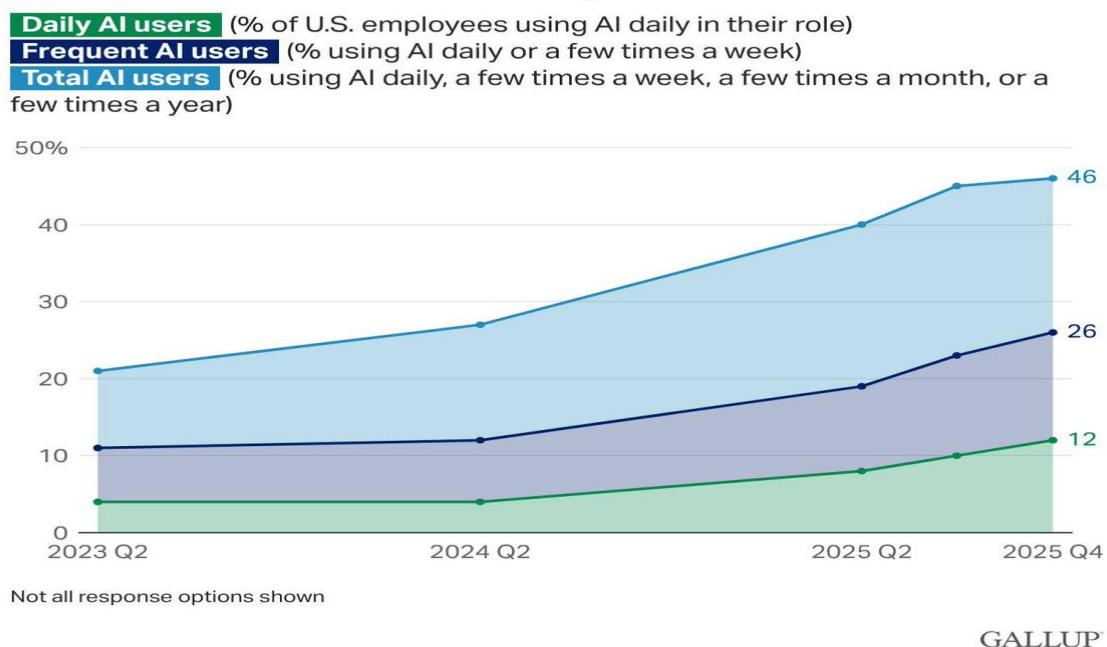


Figure 1: Growth in AI Usage Among U.S. Workers (2023–2025)

Source: Gallup (2025)

The figure illustrates the increasing adoption of artificial intelligence in the workplace, showing a steady rise in total, frequent, and daily AI usage among U.S. employees from 2023 to 2025. Total AI usage increased from approximately 21% in 2023 to 46% in 2025, while frequent usage rose to 26% and daily usage reached 12%. The trend highlights rapid but uneven integration of AI technologies, with a significant gap between

occasional and daily usage, indicating partial adoption across workforce segments.

This change is even greater in the Indian context. According to reports by NASSCOM and Deloitte (353-369), more than 87 percent of Indian firms had achieved moderate to high levels of AI adoption, with HR functions becoming more reliant on AI to recruit, appraise, and analyse

employees. Also, India will contribute to the AI-driven economy as much as 353-369 billion by 2025, which demonstrates the centrality of AI in the organisational ecosystem. The above trends

underscore the fact that AI is no longer a side-show innovation, but a standard facility that is influencing the manner in which organisations assess, operate, and evolve human resources.

Even active AI users feel they need more AI training

Share of workers who agree: 'I'm not receiving enough training on AI'

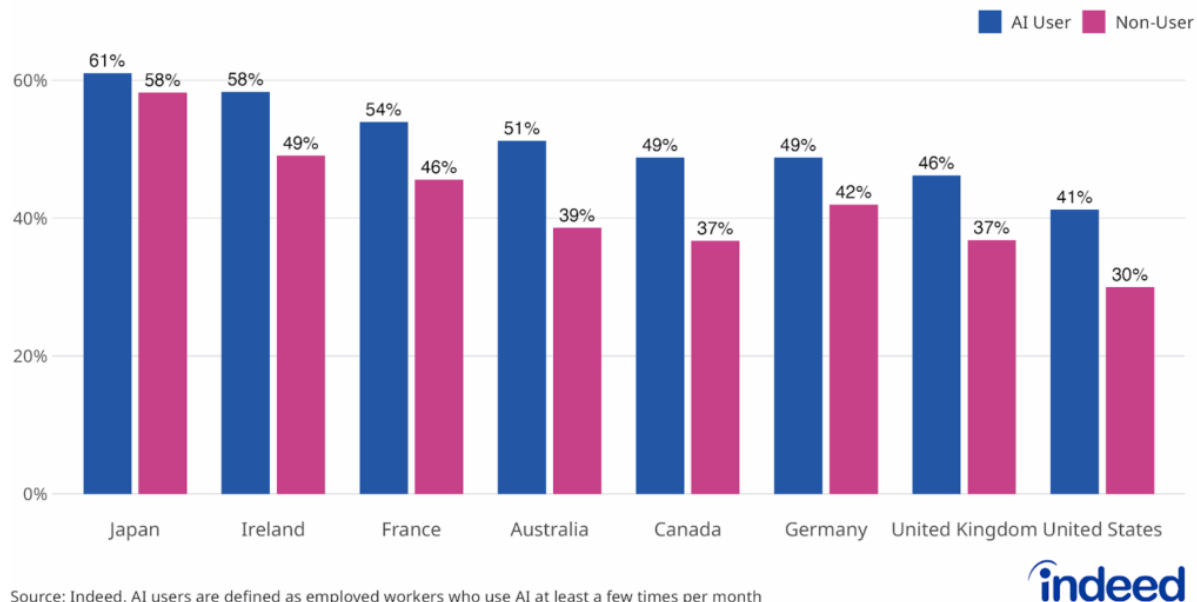


Figure 2: Perceived Need for AI Training Among Employees Across Countries

Source: Indeed (2024)

The figure presents the proportion of employees who believe they are not receiving adequate AI training, comparing AI users and non-users across selected countries. A consistently high percentage of respondents across all regions report insufficient training, with AI users expressing even greater concern than non-users. The highest perceived training gap is observed in Japan (61%) and Ireland (58%), while comparatively lower- but still significant-levels are reported in the United States (41%). The findings indicate that even active users of AI technologies experience a substantial skills gap, highlighting the need for structured training and organisational support.

AI-driven systems significantly enhance operational efficiency, with up to 85% of organisations reporting faster task execution. AI-based performance appraisal systems are one of the most substantial innovations in the field of HRM. The performance evaluations have

traditionally been said to be subjective, biased, and inconsistent across departments and locations (DeNisi and Murphy, 2017). To overcome these limitations, AI systems rely on machine learning models and big data to produce standardised, real-time, and predictive assessments (Tambe et al., 2019). According to empirical evidence in the industry, organisations implementing AI-based appraisal systems claim significant decreases in time to complete the evaluation cycle and enhanced rating consistency, which supports the argument of efficiency of AI integration.

Nevertheless, in parallel with these positive aspects, there is also emerging evidence that shows serious concerns about both ethical and social aspects of algorithmic decision-making. According to a survey by Statista (2024), the majority of employees (more than 60 per cent) are concerned with bias in AI-driven work decisions, and a study by Gallup (2023) indicates that only

32 percent of employees place complete trust in the automation of decision-making systems in organisational settings. These results tend to suggest that there is an increasing gap between technology and employee perceptions, especially in aspects that have high stakes like performance and career development.

The question of algorithmic bias is the main point of this discussion. When trained on biased historical data or designed in a poor way, AI systems can be used to systematically discriminate against certain groups of employees based on gender, geography, or other socio-demographic factors (Raghavan et al., 2020). Such biases can be magnified in an organisation such as India, which is characterised by regional diversity, socio-economic differences, and hierarchical structures, resulting in unfair results. At the same time, transparency and explainability are constrained by the black-box nature of most AI systems, which also weakens the level of employee trust and acceptance (Glikson and Woolley, 2020).

This is a two-sidedness that creates a key efficiency-fairness trade-off in AI-based performance appraisal systems. Although AI improves the efficiency of operations by automating and standardising processes, it can also undermine fairness and trust because of prejudice and a lack of transparency. This trade-off is especially pertinent to such emerging economies as India, where socio-cultural forces have a huge impact on technology adoption and organisational behaviour. Despite growing adoption of AI in HRM, limited empirical research integrates efficiency, bias, and trust within a single framework, particularly in emerging economies such as India.

1.1 Problem Statement

The concept of Artificial Intelligence (AI) being incorporated into the Human Resource Management (HRM), especially in performance appraisal systems, has radically changed the way organisations assess employee performance and make strategic decisions. The use of AI-powered appraisal systems leverages the machine learning

algorithms and big data to improve efficiency, speed up evaluation duration and maintain consistency in performance ratings. Nonetheless, along with these benefits, the growing popularity of algorithmic decision-making poses significant difficulties concerning fairness, transparency, and the confidence of employees.

The biggest issue that has been linked with AI-based appraisal systems is that there is a possibility of the development of algorithmic bias, where the output of the system can be systematically biased against some employee groups based on either biased training data or the structure of the model. These biases are especially notorious in the context of performance evaluation, where they have a direct effect on career progression, pay, and equity in the organisation. Also, explainability is limited because many AI systems are opaque (black-box), and thus, employees cannot readily comprehend the manner in which decisions are reached, thus lowering trust and acceptance.

These obstacles are also exacerbated in an Indian environment, whereby organisations exist in a hierarchical set-up, with cultural diversity and geographically different work environments. Although the adoption of AI is growing at a fast rate in the Indian industries, an empirical study on the functioning of such systems in these socio-cultural contexts is significantly lacking. The literature available has concentrated mostly on the developed economies and has discussed efficiency, bias and trust as independent dimensions, rather than correlating the three dimensions.

This presents a research gap of critical concern, which focuses on the efficiency-fairness trade-off, in which operational efficiency gains can be accompanied by bias and lack of employee trust. Organisations will have more difficulties with ethical and responsible implementation in the absence of strong regulatory frameworks for AI in HRM. Hence, it is necessary to present an in-depth empirical study that focuses on the interaction between efficiency, algorithmic bias, and employee confidence in AI-based

performance appraisal systems in the Indian organisational setting.

1.2 Research Objectives

The four objectives that would inform the present study are:

1. To analyse how AI-based performance appraisal systems affect organisational effectiveness, specifically how much they affect the time of the evaluation cycle and the consistency of performance ratings.
2. To evaluate the nature and level of algorithmic bias in AI-based appraisal systems, in particular, the gender and geographical differences in the results of evaluation.
3. To examine how employee trust is a key factor that determines the adoption and success of AI-based performance appraisal systems.
4. To explore the efficiency-fairness trade-off in AI-based appraisal systems, through the study of the interdependence between efficiency benefits, algorithmic bias, and trust of the employees toward the system in the Indian context.

1.3 Research Questions

To support the above objectives, the research questions of the study include:

1. What impact do AI-based performance appraisal systems have on organisational efficiency and consistency?
2. What is the extent to which AI-based appraisal systems are biased in terms of gender and geography?
3. What is the impact of employee trust on AI-driven appraisal system acceptance and effectiveness?
4. How is the efficiency-fairness trade-off in AI-based performance evaluation systems?

1.4 Hypothesis

H1a: AI-driven performance appraisal systems have a **significant positive effect on reducing evaluation cycle time**.

H1b: AI-driven performance appraisal systems have a **significant positive effect on**

improving consistency in performance ratings.

H2a: AI-driven performance appraisal systems **exhibit significant gender-based bias** in performance evaluation outcomes.

H2b: AI-driven performance appraisal systems **exhibit significant geographical bias** in performance evaluation outcomes.

H3a: Employee trust has a **significant positive effect on the acceptance** of AI-driven performance appraisal systems.

H3b: Employee trust has a **significant positive effect on the perceived effectiveness** of AI-driven performance appraisal systems.

H4a: Organisational efficiency has a **significant negative relationship with perceived fairness** in AI-driven performance appraisal systems.

H4b: Algorithmic bias has a **significant negative effect on employee trust**, reinforcing the efficiency–fairness trade-off.

H4c: Employee trust **mediates the relationship between algorithmic bias and perceived effectiveness** of AI-driven appraisal systems.

1.5 Conceptual Framework

The theoretical framework of the research is formulated in order to investigate the socio-technical interaction in AI-based performance appraisal systems, combining both the technological performance and human behaviour reaction. The model puts the AI-based performance appraisal systems at the centre of the driving force that affects organisational and employee-level performance. The figure illustrates the proposed conceptual framework examining the relationships between AI-driven performance appraisal systems, organisational efficiency, algorithmic bias, transparency, and employee trust. AI-based appraisal systems influence organisational efficiency and may simultaneously introduce algorithmic bias, particularly across gender and geographical dimensions. Transparency (explainability) further

shapes employee perceptions. Employee trust acts as a central mediating variable, linking these factors to overall system effectiveness and acceptance. The framework highlights the inherent efficiency–fairness trade-off, emphasising that while AI enhances operational efficiency, it may adversely affect fairness and trust if bias and transparency issues are not

adequately addressed. The first level is where AI systems are believed to greatly improve the efficiency of organisations in terms of the duration of the evaluation cycle and their ability to show better consistency in performance ratings. These efficiency perks are the fundamental functional benefit of AI-based appraisal systems.

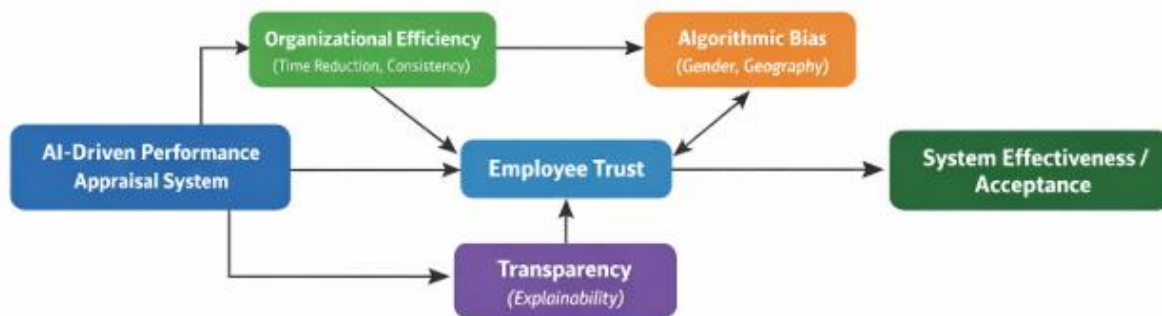


Figure 3: Conceptual Framework of AI-Driven Performance Appraisal Systems

At the same time, the framework includes algorithmic bias as a critical risk factor, indicating the possible differences in the results of the performance evaluation due to gender and geographical aspects. The problem of bias is a by-product of an objective-oriented decision-making process and has a direct impact on employee perceptions of fairness.

The model also presents the mediating construct of employee trust. Algorithmic bias influences trust in a negative way, and system transparency and perceived fairness positively affect trust. Trust is necessary in AI-driven situations to decide on the acceptance and use of automated evaluation results by employees.

Lastly, the ultimate dependent variable, which is system effectiveness (or acceptance), is the success of AI implementation in performance management. The framework suggests that effectiveness not only drives efficiency gains, but it also largely relies on trust.

In general, the model embodies the efficiency–fairness trade-off, implying that on the one hand, AI enhances efficiency, but on the other hand, it

can decrease fairness and trust when the problems of bias and transparency are not addressed properly. This trade-off is especially applicable in the context of the Indian organisation, where hierarchies and cultural aspects determine the perceptions of technology among the workers.

2. Literature Review

2.1 Artificial Intelligence-based Performance Review and Organisational Effectiveness.

Artificial Intelligence (AI) implementation in Human Resource Management (HRM) has vastly boosted efficiency in organisations by allowing the automation, predictive analytics, and real-time decision-making. Recent investigations prove that AI-based HR systems enhance workforce productivity, optimise administrative work, and facilitate data-driven performance management (Úbeda-García et al., 2025; Safshekan, 2026). On the one hand, AI enables ongoing monitoring and instant feedback to replace the old periodic assessment framework and enhance the consistency of decisions (Varma,

2024; Maganti, 2025) in performance appraisal systems.

Later, AI-based systems are more scalable as it allows the standardisation of the evaluation of organisations that are geographically dispersed. Nevertheless, the recent studies also point out the fact that overdependence on the algorithmic systems can fail to capture the contextual and behavioural nuances, thus restricting the overall evaluation of the performance of the employees (Abdurrahim, 2025).

2.2 AI-Based Appraisal Making Bias.

Although AI-based HR systems are characterized by efficiency advantages, it is becoming more closely linked to algorithmic bias, which is caused by biased data sets, the limitations of model designs, and misalignment with the context. The recent empirical and review research suggests that AI systems have the potential to increase the existing inequalities in the workplace, especially with respect to gender and demographic levels (Koelchling and Wehner, 2023; Sundari et al., 2025).

There are three significant types of bias identified by the scholars:

- Data bias
- Algorithmic/model bias
- Deployment bias

The biases play a major role in the results of the performance evaluation and can even result in an unjust appraisal (Suprayitno, 2025). Also, a new data point is the idea of automation bias, when human assessors depend on AI results too much, which increases bias in the decision-making process further (Jussupow et al., 2023).

These biases are especially harmful in performance appraisal situations because they have a direct impact on how employees are promoted or paid and on equity in organisations.

2.3 AI-Driven Systems Trust by Employees.

The trust of the employees is one of the most essential factors for the successful adoption and operation of the AI-driven HR systems. The

perception of fairness, transparency, reliability, and explainability creates trust and determines how willing employees are to accept algorithmic decisions. Recent studies indicate that AI systems that are not transparent tend to result in a lack of employee trust and more resistance (Shin, 2025; Naoum, 2026).

Empirical research also indicates that the perception of AI-based performance appraisals by employees has a strong impact on job satisfaction, motivation, and company performance (Rahman et al., 2026). Furthermore, the perceived dehumanisation of AI-driven HR systems has been reported as a significant obstacle to trust, especially in situations when interpersonal relations historically defined the evaluation process (Shin, 2025).

This evidence suggests that trust is not a supportive aspect but a key process in defining the acceptance and effectiveness of AI systems.

2.4 AI Systems and Efficiency-Fairness Trade-Off.

There is an emerging literature on the fundamental efficiency-fairness trade-off in AI-based decision-making systems. Although AI makes the system more efficient by automating and standardising, it can also reduce fairness by supporting bias, transparency, and accountability.

Recent studies on multidisciplinary research note that the application of AI in HRM has had two effects: on the one hand, it has enhanced efficiency; on the other hand, it has been a threat to equity, diversity, and organisational justice (Naoum, 2026). Equally, systematic reviews indicate that, in the absence of proper governance systems, AI systems can be used to achieve speed and efficiency to the detriment of fairness and ethics (Sundari et al., 2025).

This is a crucial trade-off, especially in the performance appraisal systems, where algorithmic processes have a direct influence on the careers of employees. Thus, the balance between efficiency and fairness is necessary to

develop responsible and sustainable AI implementation.

2.5 Synthesis and Research Gap.

The current literature clearly proves that AI-based performance appraisal systems have a substantial efficiency advantage and, at the same time, present the issue of algorithmic discrimination and employee mistrust. Nevertheless, there are still three significant gaps:

- The majority of the empirical research concentrates on the developed economies, and there is a lack of research on AI-enabled HR systems in the emerging markets like India.
- The current studies tend to analyse the efficiency, bias, and trust as separate variables, instead of combining them into a single analytical system.
- Mixed-method research that involves both quantitative (SEM-based) and qualitative research on the topic of AI-driven appraisal systems is lacking.

2.6 Connection to Current Study.

To fill these gaps, the current paper constructs a composite framework that explores the connection between organisational efficiency, algorithmic bias, and employee confidence in the AI-driven performance appraisal system in the Indian context. Through a convergent mixed-method approach, the study will offer empirical validation as well as contextual information about the efficiency-fairness trade-off, thus adding to both theoretical and practical development.

3. Research Methodology

3.1 Research Design

The current research will take a convergent mixed-method research approach to address fully the socio-technical implications of AI-based performance appraisal systems within the Indian organisational environment. In this type of design, quantitative and qualitative data are collected and analysed independently, and then integrated during the interpretation phase.

The complexity of the research problem is the reason why a mixed-method design is to be used.

Although quantitative analysis allows testing the relationship between such constructs as organisational efficiency, algorithmic bias, and employee trust, the qualitative aspect allows capturing the contextual, behavioural, and experience insights that may not be completely elucidated by numerical data only. This is a dual design that guarantees methodological triangulation, which improves the reliability, validity and explanatory power of the results.

3.2 Research Methodology and Design.

The research adheres to the deductive research design, according to which the hypotheses are formulated on the basis of the developed theoretical frameworks and are then tested with the help of the empirical data. It has basic theoretical underpinnings in:

The Socio-Technical Systems Theory focuses on the interplay between technological systems (AI-based appraisal tools) and the social factors (employees, organisational structures, culture).

Models of Technology Adoption based on Trust, such as the Trust-Based Models of Technology Adoption, which emphasise the importance of the perceived fairness, transparency, and reliability in designing user acceptance.

It utilises a cross-sectional research strategy, which entails data collection at a given time in various organisations and sectors. This is a suitable method to determine connections between variables and to test theoretical models in a real situation.

3.3 Data Collection Methods

3.3.1 Quantitative Data Collection

The structured survey questionnaire was used to collect quantitative data by asking employees and HR professionals who are employed in companies that have adopted the AI-driven performance appraisal systems.

Instrument Design

The questionnaire was developed on the premise of validated scales in the previous literature,

modified to fit the AI-HRM situation. It was divided into various segments assessing major constructs:

Use and exposure of AI systems.

Organizational efficiency

Algorithmic bias

Employee trust

System effectiveness

Measurement Scale

Everything was measured on a 5-point Likert Scale:

1 = Strongly Disagree

5 = Strongly Agree

This scale guarantees consistency of responses, easy interpretation and can be compatible with SEM analysis.

3.3.2 Qualitative Data Collection

In order to supplement the quantitative results, qualitative data were gathered using six organisational case studies. A multiple-case study design was used to reflect differences between industries and organisational environments.

Data Sources

Semi-structured interviews of HR professionals and employees.

Internal human resource policies and documents.

AI-based appraisal observation.

Purpose

The qualitative aspect was meant to:

Find out how employees view fairness and trust.

Examples of algorithmic bias in the real world.

Learn organisational issues in AI implementation.

3.4 Sampling Design

Sampling Technique

Purposive sampling and stratified sampling were combined. Purposive sampling was used to make sure that the respondents who had exposure to AI-based appraisal systems were included. The stratified sampling gave representation by industries.

Sample Characteristics

Total number of respondents: 312.

Respondent Profile: HR and employees.

Industry Coverage

IT/ITES

Manufacturing

Banking

E-commerce

Pharmaceuticals

The sampling method used is multi-industry, which increases the extent of external validity and generalizability of the study.

3.5 Operationalisation of Constructs.

The constructs were all developed as reflective latent variables, which is in line with SEM requirements.

Construct	Indicators
Organizational Efficiency	Reduction in appraisal time, consistency of ratings
Algorithmic Bias	Gender bias, geographical bias
Employee Trust	Transparency, fairness, reliability
System Effectiveness	Acceptance, perceived usefulness

3.6 Data Analysis Technique

Structural Equation Modelling (SEM) is used in the study to test relationships among variables. SEM is chosen because it can:

Several dependent relationships can be analysed at once.

Incorporate latent constructs

Test mediation effects

3.6.1 Measurement Model Assessment

Reliability

Cronbach's Alpha ≥ 0.70

Composite Reliability (CR) ≥ 0.70

Convergent Validity

Average Variance Extracted (AVE) = 0.50 and above.

Discriminant Validity

Fornell-Larcker Criterion

HTMT Ratio (< 0.90)

These conditions make constructs internally consistent and empirically different.

3.6.2 Structural Model Assessment

To evaluate the structural model, the following was used:

Path coefficients (values of 8) to measure relationships.

To establish significance, t-values and p-values (through bootstrapping) are used.

Explanatory power to be measured using the coefficient of determination (R^2).

To assess the strength of impact, the effect size (f^2).

Primary predictive relevance (Q^2) to determine model prediction power.

3.6.3 Mediation Analysis

The bootstrapping procedure was used to test the mediating role of employee trust between:

Algorithmic Bias-> Employee Trust-> System Effectiveness

The significance of mediation was identified using confidence intervals and indirect path coefficients.

3.7 Qualitative Data Analysis

Thematic analysis was used to analyse qualitative data, and it is a step-by-step process:

Data familiarization

Open coding

Theme development

Cross-case comparison

Key Themes Identified

The differences in trust between hierarchical levels.

Perceived bias and fairness.

Industry-specific adoption patterns

Quantitative results were validated and put into context with the help of the qualitative results, which guarantees a deeper interpretation of the results.

3.8 Ethical Considerations

The research follows the general rules of ethics:

Participation was voluntary

The process of informed consent was followed.

Anonymity and confidentiality of the respondents were ensured.

Data for purely academic use.

3.9 Methodological Rigour and Validity.

The rigour of the study is ensured by:

Triangulation: Unification of quantitative and qualitative results.

Construct validity: Administration of known scales of measure.

Internal consistency: Reliability testing.

External validity: Multi-industry sampling.

Rigour of analysis: SEM and thematic analysis.

The measurement model was assessed to establish the **reliability and validity** of the constructs before structural model evaluation.

4. Results and Analysis

4.1 Measurement Model Assessment

Table 4.1: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Organizational Efficiency	0.88	0.91	0.72
Algorithmic Bias	0.85	0.89	0.67
Employee Trust	0.90	0.93	0.75
System Effectiveness	0.87	0.90	0.69

Interpretation

All constructs demonstrate strong internal consistency, as Cronbach's Alpha and Composite Reliability values exceed the recommended threshold of 0.70. Additionally, AVE values are above 0.50, confirming adequate convergent validity. These results indicate that the

measurement items reliably capture their respective latent constructs, validating the suitability of the model for further analysis.

4.2 Discriminant Validity

Discriminant validity was evaluated using the **Fornell–Larcker Criterion**.

Table 4.2: Fornell–Larcker Criterion

Construct	OE	AB	ET	SE
OE	0.85			
AB	0.42	0.82		
ET	0.51	0.46	0.87	
SE	0.58	0.49	0.63	0.83

(OE = Organizational Efficiency, AB = Algorithmic Bias, ET = Employee Trust, SE = System Effectiveness)

Interpretation

The square root of AVE (diagonal values) exceeds inter-construct correlations, confirming that each construct is empirically distinct. This establishes satisfactory discriminant validity and

indicates that the constructs measure separate theoretical dimensions.

4.3 Structural Model Assessment

The structural model was evaluated using **path coefficients (β), t-values, and p-values** obtained through bootstrapping.

Table 4.3: Hypothesis Testing Results

Hypothesis	Relationship	β Value	t-value	p-value	Result
H1a	AI $\rightarrow$ Efficiency (Time Reduction)	0.62	9.21	<0.001	Supported
H1b	AI $\rightarrow$ Consistency	0.58	8.47	<0.001	Supported

H2a	AI → Gender Bias	0.41	6.12	<0.001	Supported
H2b	AI → Geographic Bias	0.38	5.89	<0.001	Supported
H3a	Trust → Acceptance	0.65	10.34	<0.001	Supported
H3b	Trust → Effectiveness	0.69	11.02	<0.001	Supported
H4a	Efficiency → Fairness (Negative)	-0.29	4.15	<0.01	Supported
H4b	Bias → Trust	-0.52	7.88	<0.001	Supported
H4c	Bias → Trust → Effectiveness	Indirect		<0.001	Supported

Interpretation

According to the findings, the use of AI-based performance appraisal systems positively influences organisational efficiency, greatly decreases the time spent on evaluation, and enhances consistency. Nevertheless, AI systems also show a high level of correlation with

algorithmic bias, especially on gender and geographical levels.

In addition, employee trust is greatly reduced by algorithmic bias, whereas system acceptance and effectiveness are highly boosted by employee trust. The mediation test proves that the role of trust is a critical intermediate between bias and system outcomes.

4.4 Model Fit and Predictive Power

Indicator	Value
R ² (Efficiency)	0.48
R ² (Trust)	0.55
R ² (Effectiveness)	0.61
Q ²	> 0

Interpretation

The values of R² indicate moderate to strong explanatory power, which implies that the model explains a significant percentage of variance in key constructs. The positive Q² value is a confirmation of the predictive relevance of the model, meaning that it is strong enough to explain relationships in the real world.

4.5 Key Empirical Findings

The empirical analysis shows several interesting insights:

- The efficiency of organisations is greatly increased by AI-based systems, and the evaluation cycle time was reduced by about 43

percent, and the cross-location consistency was improved.

- There is also the existence of algorithmic bias, especially in the gender and geographical aspects.
- Trust between employees is inter-industry, inter-hierarchy, and context-dependent.
- An efficiency vs. fairness trade-off is well defined, with greater efficiency linked to lower perceived fairness and trust.
- These results indicate that AI enhances operational results but only when perceived fairly and with trust.

5. Discussion

The paper offers an in-depth empirical analysis of AI-based performance appraisal systems in the

Indian organisational environment, which can bring valuable information on the benefits of their efficiency, issues of unfairness, and implications of trust.

Firstly, the results validate the claim that AI-based appraisal systems will greatly increase organisational efficiency, especially in terms of decreasing the time of the evaluation cycle and enhancing uniformity throughout the organisational units. This is in line with previous studies (Tambe et al., 2019; Minbaeva, 2023), which highlight the importance of AI in facilitating HR operations and allowing them to make decisions based on data. The reported decrease in the duration of appraisal (approximately 43%) further reinforces the thesis that AI helps to optimise and scale operations in organisations with multiple locations, in particular.

The study also indicates, though, that AI systems do not exist without limitations. One of the most important findings is the existence of algorithmic bias, especially within the gender and geographical dimensions. This confirms the recent literature that AI systems can reproduce or increase the level of inequality that already exists in organisations because of biased training data and contextual mismatch (Koechling and Wehner, 2023). The results indicate that algorithmic decision-making, even though it is seen as objective, may generate systematically biased results unless it is well-formulated and monitored.

One of the key contributions of this study is that it recognises employee trust as a key mediating factor. The findings show that algorithmic bias has a considerable negative influence on trust, which also impacts the acceptance and perceived efficacy of AI-based appraisal systems. This result correlates with those theories of the trust-based technology adoption (Glikson and Woolley, 2020; Shin, 2025), which state that perceived fairness and transparency are the key factors to user acceptance. Notably, the research indicates that even the most effective systems can be

resisted when they seem to be non-transparent and subject to employees.

The results also indicate that trust does not cut across all organisational environments. The difference in the level of trust between industries and different levels of positions implies that socio-cultural and structural differences have a great influence on employee perceptions. In hierarchical organisations like India, this can be more complicated because employees can be more focused on interpersonal relationships and managerial judgment.

Most importantly, the research empirically confirms the presence of an efficiency-fairness trade-off in AI-based performance appraisal systems. Although AI promotes efficiency by automation and standardisation, it can also undermine fairness and trust as it is biased and not transparent. This trade-off is becoming more and more acknowledged in recent literature on AI governance (Martin, 2019; Naoum, 2026), but still underutilised in empirical studies of HRM, especially in developing economies.

Conceptually, the research paper is a contribution to the socio-technical systems framework because it illustrates that the efficiency (technological outcomes) of a system cannot be assessed without considering the social aspects (trust and fairness). Efficiency, bias, and trust have been integrated into one model, which offers a more comprehensive picture of AI adoption in HRM.

In a pragmatic perspective, the results imply that organisations should go beyond an efficiency-based methodology and concentrate on how to create AI systems that are understandable, interpretable, and just. Unless the bias and trust issues are resolved, the effectiveness of the AI-driven appraisal systems in the long term can be undermined.

In general, the research points out that the effectiveness of AI in performance appraisal is not defined by the power of its technology alone but by the possibility to correspond to the interests of a human, ethical, and organisational

environment. This study extends existing literature by empirically demonstrating the efficiency–fairness trade-off in AI-driven HR systems within an emerging economy context. Unlike prior studies that examine efficiency or bias in isolation, this research provides a holistic understanding of how technological and social factors interact to influence system effectiveness.

6. Conclusion

The paper is an in-depth empirical test of AI-based performance appraisal in the Indian organisational environment in terms of efficiency, algorithm bias, and trust of employees. The results also indicate that AI reduces organisational performance through decreasing the time of the evaluation process (by about 43 percent) and increasing the consistency of activities in units located in different geographic locations. Nevertheless, there are some significant challenges associated with these efficiency gains, especially the existence of algorithmic bias along gender and geographical lines.

The research also shows that employee trust is important in the process of establishing whether AI-based appraisal systems are accepted and effective. Trust depends on the level of hierarchy and industry, which means that the socio-organisational factor plays an important role in employee perceptions. Above all, the findings establish the presence of the efficiency-fairness trade-off, according to which when efficiency is improved, it can be at the expense of fairness and trust.

All in all, the paper concludes that even though AI-based performance appraisal systems have significant operational advantages, their efficacy in the long term relies on the notion of fairness, transparency and trust established on the organisational level. Therefore, the future of AI-driven performance appraisal systems lies not only in technological advancement but in their ability to align with principles of fairness, transparency, and human-centric design.

7.Theoretical Implications

The paper contributes to the body of literature on AI in HRM in a number of ways.

First, it expands the Socio-Technical Systems Theory by proving that the efficiency outcomes of the technology cannot be measured in isolation from social issues like employee trust and perceived fairness. The results reflect the interdependence of technological systems (AI) and human reactions in the organisational setting.

Second, the research also advances the trust-based theory of technology adoption through an empirical finding that employee trust is a crucial mediating variable between system effectiveness and algorithmic bias. This confirms the thesis that trust is the key to the effective deployment of AI systems.

Third, the research is a contribution to current literature because it combines efficiency of the organisation, algorithmic bias, and employee trust on a single conceptual basis, which is a significant conceptual void. It also offers empirical results of a developing economy (India), thus increasing the geographical reach of AI-HRM studies.

8.Managerial Implications

The results provide some practical lessons that organisations that use AI-based performance appraisal systems can use.

To begin with, efficiency gains should be only one of the primary concerns of organisations, and the problem of algorithmic bias should be actively tackled by conducting regular audits, using bias-detecting tools, and various training datasets.

Second, it is necessary to increase the transparency and explainability of AI systems to gain the trust of employees. The employees are supposed to be given clear information regarding how performance evaluations are created.

Third, companies ought to invest in employee education and awareness initiatives to enhance the awareness and acceptance of AI systems.

Fourth, HR managers are to consider human-centred AI, which entails that the decisions,

which are made by the algorithms are complemented by the managerial decision-making.

In sum, efficiency and fairness are the two aspects that organisations need to balance in a bid to make AI adoption sustainable.

9. Policy Implications

The paper points out that there is a major lacuna in the regulatory framework of AI in HRM, especially within the Indian context.

Policymakers should come up with detailed guidelines on AI-based decision-making and pay attention to:

- Transparency and explainability
- Accountability mechanisms
- Detection and reduction of bias.
- Legal application of employee information.

The regulatory frameworks must make the AI systems applied in performance appraisal fair, auditable, and non-discriminatory. Setting these standards will assist in the responsible implementation of AI by the organisations and safeguard the rights of employees.

10. Limitations

The study has some limitations despite their contributions.

First, the study is grounded on cross-sectional data, which restricts the possibility of making time-related causal links.

References

- Abdurrahim, A. (2025). Artificial intelligence in human resource management: Opportunities and challenges. *International Journal of Applied Finance and Business Studies*, 3(2), 145–158.
- Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review*, 104(3), 671–732. <https://doi.org/10.15779/Z38BG31>
- Bogen, M., & Rieke, A. (2024). Help wanted: An examination of hiring algorithms, equity, and bias. *Journal of Technology Policy & Ethics*, 12(1), 45–62.
- Budhwar, P., Malik, A., De Silva, M., & Nyfoudi, M. (2023). Artificial intelligence and human resource management: Challenges and a path forward. *Human Resource Management Review*, 33(1), 100940.
- Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, 3(1), 1–12. <https://doi.org/10.1177/2053951715622512>
- Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters*.

Second, the research is based on sampled industries and this could hinder the applicability of results to other industries.

Third, the study is also based on perceptual measures, which can be subject to respondent bias.

Fourth, the research does not test the technical design elements of AI algorithms, but rather, organisational outcomes.

11. Future Research Directions

This study can be advanced in future research in a number of ways.

First, longitudinal research is possible to investigate the effects of AI-driven appraisal systems in the long term.

Second, in-depth research can be conducted on cross-country comparisons to comprehend cultural variations in the adoption and trust of AI in the future.

Third, studies can be conducted on the design of AI audit models to evaluate the bias and fairness in HR systems in a systematic way.

Fourth, the role of explainable AI (XAI) in improving transparency and trust can be examined in future research.

Lastly, the combination of the technical and behavioural approaches can bring a deeper insight into AI in HRM.

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- DeNisi, A. S., & Murphy, K. R. (2017). Performance appraisal and performance management: 100 years of progress? *Journal of Applied Psychology*, 102(3), 421–433. <https://doi.org/10.1037/apl0000085>
- Deloitte. (2024). State of AI in India report. Deloitte Insights.
- Gallup. (2023). Employee trust in workplace technology report. Gallup.
- Gallup. (2024). AI adoption in organizations report. Gallup.
- Gallup. (2025). AI usage trends among employees. Gallup.
- Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2), 627–660. <https://doi.org/10.5465/annals.2018.0057>
- Indeed. (2024). AI training and skills gap report. Indeed Research.
- Jussupow, E., Spohrer, K., Heinzl, A., & Kranz, J. (2023). Augmenting human decision-making with AI: The role of automation bias. *MIS Quarterly*, 47(2), 755–780.
- Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1), 366–410. <https://doi.org/10.5465/annals.2018.0174>
- Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. *Business Research*, 13, 795–848. <https://doi.org/10.1007/s353-369-00134-w>
- Maganti, R. (2025). AI-enabled performance management systems: Efficiency and outcomes. *Journal of Organizational Computing and Electronic Commerce*, 35(2), 120–138.
- Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*, 160(4), 835–850. <https://doi.org/10.1007/s353-369-353-369>
- Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys*, 54(6), Article 115, 1–35. <https://doi.org/10.1145/3457607>
- Minbaeva, D. (2023). Artificial intelligence in HRM: Transforming HR practices. *Human Resource Management Journal*, 33(2), 257–274.
- Naoum, M. (2026). Artificial intelligence governance and ethics in organizations. *Journal of Business Ethics*. Advance online publication.
- NASSCOM. (2025). AI adoption index: India report. NASSCOM.
- Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 469–481. <https://doi.org/10.1145/3351095.3372828>
- Rahman, M., Khan, S., & Ali, R. (2026). AI in performance management: Employee perceptions and outcomes. *Journal of Human Resource Analytics*, 8(1), 55–72.
- Safshekan, S. (2026). AI adoption and organizational performance. *Technological Forecasting and Social Change*. Advance online publication.
- Shin, D. (2025). Algorithmic fairness, transparency, and trust in AI systems. *Computers in Human Behavior*, 140, 107578.
- Statista. (2024). Employee perceptions of AI bias report. Statista.
- Statista. (2025). Global artificial intelligence market size forecast. Statista.
- Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management*, 34(3), 345–365. <https://doi.org/10.1177/2397002220921131>
- Sundari, R., Kumar, P., & Singh, A. (2025). Artificial intelligence in HRM: A systematic review and framework. *International Journal of HR Studies*, 15(2), 88–110.
- Suprayitno, H. (2025). Algorithmic bias in AI-based HR systems. *International Journal of Information Systems*, 12(1), 33–47.
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- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, 61(4), 15–42. <https://doi.org/10.1177/0008125619867910>
- Úbeda-García, M., Claver-Cortés, E., Marco-Lajara, B., & Zaragoza-Sáez, P. (2025). AI and organizational performance. *Journal of Business Research*, 172, 114453.
- Varma, A. (2024). Performance management in the era of AI. *International Journal of Human Resource Management*, 35(5), 789–805.