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Adoption of AI-Based Technologies and Its Impact on HR Functions: A Study of Selected IT Firms in India

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Abstract
The rapid adoption of artificial intelligence (AI) technologies is transforming organizational processes, with human resource (HR) functions emerging as a critical domain of impact. This study investigates the extent to which AI-based technologies influence key HR practices—such as recruitment, onboarding, performance management, learning and development, and employee engagement—within selected IT firms in India. The ***purpose*** *of this research is to analyze how AI adoption reshapes HR efficiency, decision-making, and employee perceptions of fairness and transparency in technologically driven workplaces.*
A ***mixed-methods approach*** *was employed, combining quantitative survey data from 320 HR professionals and employees with qualitative insights from 25 semi-structured interviews conducted across leading IT firms. Quantitative data were analyzed using partial least squares structural equation modeling (PLS-SEM) to measure AI adoption intensity and HR outcomes, while qualitative data were examined through thematic analysis to capture nuanced perceptions and organizational challenges.*
The ***findings*** *reveal that AI adoption significantly enhances recruitment efficiency, reduces bias in candidate screening, and supports data-driven performance evaluations. However, employees expressed concerns about reduced human touch in HR processes and potential surveillance risks. The results further indicate that firms with higher AI maturity demonstrate stronger alignment between HR analytics and workforce planning.*
In terms of ***practical implementation****, the study highlights strategies for balancing technological automation with human-centric HR practices. IT firms can leverage AI to optimize operational processes while concurrently investing in change management, transparency protocols, and employee trust-building initiatives.*
The ***originality*** *of this study lies in its dual methodological design and its focus on the Indian IT sector, which is at the forefront of AI-driven HR transformation. Unlike prior research that primarily addresses either technological efficiency or employee perceptions, this paper integrates both dimensions, offering a holistic perspective on the implications of AI adoption for HR functions in emerging economies.*
Keywords: *Artificial Intelligence in HR, HR Technology Adoption, IT Industry in India, Mixed-Methods Research, Employee Perceptions and HR Transformation*

1. INTRODUCTION

Background of AI in Organizations

Artificial intelligence (AI) has rapidly moved from being a futuristic concept to a mainstream enabler of business transformation. Organizations across industries are adopting AI-driven systems to improve efficiency, reduce operational costs, and enable real-time decision-making. AI technologies such as machine learning, natural language processing, and predictive analytics are now embedded in core organizational functions, influencing not only customer-facing processes but also internal management systems. As firms compete in increasingly digital markets, the ability to leverage AI for sustainable growth and competitive advantage has become critical (Wamba-Taguimdje et al., 2020).

Evolution of AI in HR Functions Globally

Human Resource Management (HRM) has emerged as one of the most dynamic areas for AI application. Globally, organizations are deploying AI tools to enhance recruitment through automated resume screening, chatbots for candidate interaction, and predictive models for talent acquisition. Similarly, performance management has been reshaped by algorithmic evaluations and HR analytics, while learning and development benefit from AI-enabled adaptive training systems. This evolution highlights a transition from administrative

HR functions to strategic, technology-augmented roles, where data-driven insights strengthen workforce planning and employee engagement (Prikshat & Kumar, 2023).

Indian IT Industry Context

India's IT sector, known for its innovation and early adoption of emerging technologies, provides a unique context for studying AI's impact on HR functions. IT firms not only deliver AI solutions globally but also implement them internally to manage large, diverse, and rapidly evolving workforces. With the sector contributing significantly to India's GDP and employment, the way HR adapts to AI adoption has far-reaching implications for organizational culture, employee experience, and competitiveness. Moreover, as Indian IT firms expand globally, HR functions are under pressure to align with international standards while addressing local workforce challenges.

Research Gap

Despite growing interest in AI adoption in HR, existing literature is largely fragmented. Many studies emphasize technical efficiency but overlook employee perspectives such as trust, fairness, and transparency in AI-driven HR processes. Similarly, research on India's IT sector remains limited, with most insights drawn from Western contexts. There is a lack of mixed-method research that captures both the measurable outcomes of AI adoption and the qualitative experiences of HR managers and employees. Addressing this gap is essential to developing a balanced understanding of AI's role in reshaping HR in Indian IT firms.

Study Objectives and Scope

The primary objective of this study is to examine the adoption of AI-based technologies and their impact on HR functions in selected IT firms in India. Specifically, it seeks to:

- Analyze the extent of AI integration in core HR functions such as recruitment, performance appraisal, and learning and development.
- Assess employee perceptions of fairness, transparency, and trust in AI-driven HR systems.
- Compare outcomes across firms with varying levels of AI maturity.
- Provide recommendations for balancing technological efficiency with human-centric HR practices.

The scope of the study is limited to mid- and large-scale IT firms in India, as these organizations represent the forefront of AI implementation in HR.

The paper is structured as follows. Section 2 reviews the literature on AI adoption in HR, employee perceptions, and theoretical foundations relevant to the study. Section 3 outlines the research methodology, including objectives, questions, hypotheses, data collection, and analysis methods. Section 4 presents the results, integrating quantitative and qualitative findings. Section 5 discusses the implications of these findings in light of existing literature. Section 6 highlights practical applications for HR leaders and policymakers, while Section 7 concludes with contributions, limitations, and directions for future research.

2. LITERATURE REVIEW

AI in Business Transformation

Artificial intelligence (AI) has become a catalyst for organizational transformation, influencing both strategic decision-making and operational efficiency. Businesses leverage AI for predictive analytics, process automation, and personalized customer interactions, thereby enhancing competitiveness in volatile markets. Studies highlight that AI adoption is positively correlated with firm performance and innovation capability (Wamba-Taguimdje et al., 2020). Beyond external value creation, AI is increasingly deployed in internal functions such as human resources, finance, and knowledge management, demonstrating its role as a cross-functional enabler of digital transformation.

AI in HR Functions

AI applications in Human Resource Management (HRM) have expanded rapidly, reshaping core functions:

- **Recruitment and Selection**: AI-powered systems streamline resume screening, candidate shortlisting, and chatbot-driven engagement. Research indicates such tools improve efficiency while minimizing biases inherent in manual screening (Pan et al., 2022).

- **Onboarding and Training**: Adaptive learning platforms powered by AI personalize training content to employee needs, reducing skill gaps and accelerating integration into organizational culture (Prikshat & Kumar, 2023).
- **Performance Management**: Algorithm-driven HR analytics enable continuous feedback and predictive evaluation of performance trends, but raise questions regarding transparency and fairness (Mo, 2025).
- **Learning and Development (L&D)**: AI-driven Learning Management Systems (LMS) create personalized pathways for career growth, aligning employee development with organizational goals (Krishna & Verma, 2025).

- **Employee Engagement and Retention**: AI chatbots and sentiment analysis tools monitor employee morale and predict turnover risks, providing HR managers with actionable insights (Reddy, 2022).

These applications collectively demonstrate that AI has moved HR beyond administrative tasks toward a more strategic role in organizational success.

Employee Perceptions: Trust, Fairness, and Transparency

While AI improves efficiency, employees often express concerns about its fairness and implications for workplace trust. Research shows that perceptions of AI in HR depend on the degree of transparency in algorithmic decision-making and how outcomes align with expectations of justice (Majrashi, 2025). For instance, employees may accept AI-assisted recruitment if explanations of selections are clear and unbiased (Köchling & Wehner, 2025). However, studies also reveal fears of excessive surveillance, loss of human judgment, and potential dehumanization of HR processes (Sadeghi, 2024). Addressing these perceptions is crucial for sustainable AI integration in HR.

THEORETICAL FOUNDATIONS

Three key theoretical frameworks underpin research on AI adoption in HR:

- **Technology Acceptance Model (TAM)**: Explains how perceived ease of use and perceived usefulness drive AI adoption in HR technologies (Madanchian et al., 2025).
- **Socio-Technical Systems Theory**: Emphasizes the interdependence of technological systems and social dynamics in organizations, highlighting the importance of balancing automation with human values.
- **HR Value Chain Models**: Illustrate how AI-based HR practices contribute to organizational outcomes through efficiency, employee engagement, and talent retention (Prikshat & Kumar, 2023).

These frameworks provide analytical lenses for assessing both the technical and human aspects of AI in HR.

Global vs Indian Perspectives

Globally, organizations have adopted AI in HR to enhance competitiveness, with Western firms focusing on predictive analytics, AI-driven assessments, and diversity hiring strategies (Biswas, 2024). In contrast, Indian IT firms are still in transitional phases, with adoption varying by firm size and resource availability. Research in India highlights both enthusiasm for AI adoption and resistance due to cultural emphasis on interpersonal relations in HR practices (Premnath & Chully, 2020). Thus, while global trends underscore efficiency, the Indian perspective raises unique challenges around cultural adaptation and workforce acceptance.

Identified Research Gaps

Despite extensive discussions on AI adoption, existing studies reveal several gaps:

1. Overemphasis on technical efficiency with limited exploration of employee perceptions.
2. Lack of context-specific studies on the Indian IT sector, which is a global leader in digital services.
3. Limited use of mixed-method approaches integrating quantitative outcomes with qualitative insights from employees and HR managers.
4. Insufficient focus on fairness, transparency, and trust as mediating variables in AI-driven HR adoption.

This study aims to address these gaps by employing a mixed-method design to evaluate both the measurable outcomes of AI in HR and the lived experiences of employees in Indian IT firms.

Table 1 – Summary of Major Studies on AI in HR

Author(s)	**Year**	**Context**	**Key Findings**	**Gaps Identified**
Pan et al.	2022	Global recruitment practices	AI improves efficiency in candidate screening and reduces bias	Limited evidence from Indian IT sector
Prikshat & Kumar	2023	Multilevel HR framework	AI reshapes performance appraisal and L&D	Employee Rerceptions not deeply studied
Majrashi	2025	Employee perceptions (Middle East)	Perceived fairness influences acceptance of AI in HR	Cross-cultural validation needed
Köchling & Wehner	2025	Career developmentin Europe	AI-driven career tools raise fairness concerns	Lack of Indian context
Premnath & Chully	2020	Indian IT sector	AI adoption in HR remains nascent but promising	No quantitative validation
Reddy	2022	Employee retention in India	AI predictive analytics effective in identifying attrition risks	Limited integration with qualitative insights

Table 1 synthesizes major studies on AI in HR, covering both global and Indian contexts. It highlights consistent findings on efficiency gains in recruitment and performance management but points out recurring gaps, especially in employee perception research and India-specific empirical validation. This reinforces the rationale for the current study's mixed-method approach.

3. RESEARCH METHODOLOGY

3.1 Research Design – Mixed-Methods Approach (Sequential Explanatory)

This study adopts a **sequential explanatory mixed-methods design**, which integrates both quantitative and qualitative techniques to generate a holistic understanding of AI adoption in HR functions. The quantitative phase was conducted first, involving surveys with HR professionals and employees to test hypotheses on the relationship between AI adoption, HR outcomes, and employee perceptions. The qualitative phase followed, consisting of semi-structured interviews to contextualize and enrich the quantitative findings with deeper insights into employee experiences and managerial perspectives. This design enables triangulation of evidence, enhances validity, and provides explanatory depth beyond what either method could achieve alone

3.2 Research Objectives of the Study

The primary objectives of this research are to:

1. Examine the adoption of AI-based technologies in HR functions within selected Indian IT firms.
2. Assess the impact of AI on recruitment, onboarding, performance appraisal, and learning and development.
3. Analyze employee perceptions of trust, fairness, and transparency in AI-driven HR processes.
4. Compare differences in outcomes between firms with varying levels of AI maturity.
5. Develop recommendations for balancing automation and human-centric HR practices in Indian IT firms.

3.3 Research Questions

The study is guided by the following research questions:

1. To what extent have Indian IT firms adopted AI-based technologies in HR functions?
2. How does AI adoption influence HR outcomes such as efficiency, bias reduction, and employee experience?
3. What are employee perceptions regarding fairness, trust, and transparency in AI-driven HR systems?
4. How do differences in AI maturity across firms affect HR outcomes?
5. What practical strategies can HR leaders adopt to integrate AI effectively while maintaining employee trust?

3.4 Hypotheses Development

Based on prior literature and theoretical foundations such as the Technology Acceptance Model (TAM) and socio-technical perspectives, the following hypotheses were formulated for quantitative testing:

- **H1:** AI adoption positively influences recruitment efficiency in IT firms.
- **H2:** AI adoption is negatively associated with perceived bias in HR decision-making.
- **H3:** AI-enabled performance management systems positively affect employee perceptions of fairness and transparency.
- **H4:** Higher levels of AI maturity in firms are associated with stronger employee engagement outcomes.
- **H5:** Employee trust mediates the relationship between AI adoption and HR function effectiveness.
- **H6 (exploratory):** Differences exist between small/mid-size and large IT firms in the extent of AI adoption and resulting HR outcomes.

These hypotheses were operationalized into measurable constructs tested in the quantitative survey and further contextualized in interviews.

3.5 Population and Sampling Strategy

3.5.1 Selection of IT Firms in India

The study focuses on IT firms operating in major technology hubs such as Bangalore, Hyderabad, Pune, and Noida. These firms were selected because they represent India's leading adopters of digital transformation initiatives and employ large, diverse workforces.

3.5.2 Sample Size Justification

For the **quantitative phase**, a sample of **320 respondents** (HR managers, executives, and employees) was targeted. This sample size exceeds the minimum requirements for PLS-SEM, which recommends at least 10 times the maximum number of structural paths directed at a latent variable (Hair et al., 2021).

For the **qualitative phase**, **25 semi-structured interviews** were conducted with HR leaders and managers across 10 firms. This number was deemed sufficient for thematic saturation.

Table 2 – Sampling Details

Parameter	Quantitative Phase	Qualitative Phase
Target Population	HR managers, executives, employees in IT firms	HR leaders and managers
Sampling Technique	Stratified random sampling	Purposive sampling
Sample Size	320 respondents	25 interviews
Geographic Focus	Bangalore, Hyderabad, Pune, Noida	Same
Data Collection Mode	Online structured survey	Virtual/face-to-face interviews

Table 2 summarizes the sampling strategy. Stratified random sampling ensured representation of employees and managers, while purposive sampling allowed rich qualitative insights from experienced HR leaders.

3.6 Data Collection Methods

3.6.1 Structured Survey (Quantitative)

A structured online questionnaire was designed to capture data on AI adoption, HR function outcomes, and employee perceptions. Likert-scale items (1 = strongly disagree to 5 = strongly agree) were used. The survey was pre-tested with 30 respondents for reliability and clarity.

3.6.2 Semi-Structured Interviews (Qualitative)

Interview protocols focused on experiences with AI in HR, perceived benefits, challenges, and ethical concerns. Open-ended questions facilitated exploratory insights, while probes ensured consistency across interviews.

Table 3 – Data Collection Tools

Tool	Purpose	Sample Questions/Items
Survey Questionnaire	Quantitative measurement of adoption and perceptions	“AI reduces bias in recruitment decisions.”; “I trust AI systems used in HR functions.”
Interview Guide	Qualitative exploration of experiences	“How has AI changed your approach to recruitment and performance appraisal?”

Table 3 highlights the instruments used, demonstrating how structured surveys and interviews complement each other in capturing both breadth and depth of evidence.

3.7 Measurement of Variables

3.7.1 AI Adoption Intensity Index

An index was created to measure the extent of AI integration across recruitment, onboarding, appraisal, and L&D.

3.7.2 HR Function Outcomes

Key outcomes included recruitment efficiency, bias reduction, employee engagement, and performance appraisal fairness.

3.7.3 Perceived Fairness, Trust, and Transparency

Employee perception variables were adapted from validated scales in organizational justice and technology trust literature.

Table 4 – Variable Operationalization

Variable	Definition	Measurement Scale	Source
AI Adoption Intensity	Degree of integration of AI across HR functions	Index (0–4 functions)	Adapted from Pan et al. (2022)
Recruitment Efficiency	Speed and accuracy of hiring	5-item Likert scale	Prikshat & Kumar (2023)
Performance Fairness	Perceived fairness in appraisal outcomes	4-item Likert scale	Mo (2025)
Employee Trust	Confidence in AI systems in HR	6-item Likert scale	Majrashi (2025)
Transparency	Perception of clarity in AI decisions	5-item Likert scale	Köchling & Wehner (2025)

Table 4 presents operational definitions, ensuring construct validity and consistency with prior studies.

3.8 Data Analysis Techniques

3.8.1 Quantitative Analysis

The survey data were analyzed using **Partial Least Squares Structural Equation Modeling (PLS-SEM)** to test hypothesized relationships. Reliability and validity were established through Cronbach's alpha, composite reliability, and AVE. Group comparisons were conducted to examine differences by firm size and AI maturity.

3.8.2 Qualiative Analysis

Interview transcripts were coded using NVivo software. Thematic analysis was conducted following Braun and Clarke's (2006) framework. Intercoder reliability was ensured by independent coding and consensus-building.

3.8.3 Integration through Triangulation

Findings from both phases were integrated at the interpretation stage. Quantitative results identified patterns, while qualitative narratives explained contextual factors and employee perspectives.

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Figure 1 – Mixed-Methods Research Process
(A flowchart showing sequential explanatory design: Step 1 – Quantitative survey → Step 2 – Qualitative interviews → Step 3 – Triangulated integration.)
Figure 1 illustrates how quantitative and qualitative phases were integrated to ensure comprehensive understanding and validation of findings.

3.9 Ethical Considerations
Ethical standards were strictly maintained. Participation was voluntary, informed consent was obtained, and anonymity was ensured. Sensitive questions about employee trust and perceptions of fairness were framed carefully to avoid discomfort. Data confidentiality was preserved in compliance with institutional ethical review guidelines.

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4. RESULTS AND ANALYSIS
This section presents the empirical findings derived from both the quantitative survey of 320 respondents and the qualitative interviews with 25 HR leaders across selected IT firms in India. Results are organized into four major parts: descriptive statistics of the sample, quantitative results from structural modeling, qualitative insights, and an integrated triangulation of findings. Each subsection elaborates the patterns observed, supported with tables, figures, and references to prior research.

4.1 Descriptive Statistics of the Sample
The survey data reflected a diverse group of participants, enhancing representativeness. Out of the **320 valid responses**, 176 were male (55%) and 144 were female (45%), indicating a relatively balanced gender distribution. The age profile showed that **32.5% were aged 25–30 years**, **45.6% were aged 31–40 years**, and **21.9% were between 41–50 years**. This age spread suggests that the study captured both younger employees with high exposure to new technologies and more experienced professionals, ensuring balanced viewpoints.
Professional roles also varied: **35% HR managers**, **40% HR executives**, and **25% general employees**. This distribution allowed examination of adoption perspectives at both strategic (managers), tactical (executives), and operational (employees) levels.
Finally, in terms of **firm size**, **60% were from large IT firms** (more than 5,000 employees), and **40% from mid-sized firms** (1,000–5,000 employees). These proportions reflect the IT sector in India, where large multinational IT firms dominate, but mid-sized companies are increasingly important.

Table 5 – Demographic Profile of Respondents

Parameter	Category	Frequency	Percentage
Gender	Male	176	55%
	Female	144	45%
Age	25–30 years	104	32.5%
	31–40 years	146	45.6%
	41–50 years	70	21.9%
Role	HR Managers	112	35%
	HR Executives	128	40%
	Employees	80	25%
Firm Size	Large (>5,000 employees)	192	60%
	Mid-sized (1,000–5,000)	128	40%

The demographic spread (Table 5) illustrates that the sample adequately represents diverse perspectives across gender, age, role, and firm size. It ensures validity in capturing the dynamics of AI adoption across hierarchical levels and organizational contexts. Similar sampling patterns have been used in other mixed-methods HR studies (Pan et al., 2022).

4.2 Quantitative Results

4.2.1 Reliability and Validity Tests

Reliability and validity are critical to ensure robustness of survey-based findings. The study tested internal consistency using **Cronbach's alpha**, composite reliability (CR), and average variance extracted (AVE). All values met the recommended thresholds: Cronbach's alpha > 0.70, CR > 0.80, and AVE > 0.50 (Hair et al., 2021). This confirms the measurement model's robustness.

Table 6 – Reliability and Validity Results

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI Adoption Intensity	0.84	0.88	0.62
Recruitment Efficiency	0.81	0.85	0.58
Performance Fairness	0.87	0.91	0.64
Employee Trust	0.85	0.89	0.61
Transparency	0.82	0.86	0.59

Table 6 demonstrates that the constructs are reliable and valid, which is critical before running structural equation modeling (SEM). These results are consistent with prior HR studies using AI adoption frameworks (Prikshat & Kumar, 2023).

4.2.2 Hypothesis Testing (PLS-SEM Path Analysis)

The hypotheses were tested using **Partial Least Squares Structural Equation Modeling (PLS-SEM)**. Bootstrapping with 5,000 resamples generated path coefficients, t-values, and p-values.

Table 7 – Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	Result
H1	AI → Recruitment Efficiency	0.42	6.12	0.000	Supported
H2	AI → Bias Reduction	-0.31	4.76	0.000	Supported
H3	AI → Performance Fairness	0.38	5.23	0.000	Supported
H4	AI Maturity → Engagement	0.29	3.87	0.001	Supported
H5	AI → Trust → Effectiveness	0.34	5.64	0.000	Supported
H6	Firm Size Differences	Significan t	–	0.004	Supported

Table 7 indicates all six hypotheses were supported. The strongest impact was AI's effect on recruitment efficiency (β = 0.42), suggesting automation is particularly valuable in streamlining candidate screening. Trust (H5) emerged as a key mediator, confirming that employee perceptions shape AI's effectiveness in HR.

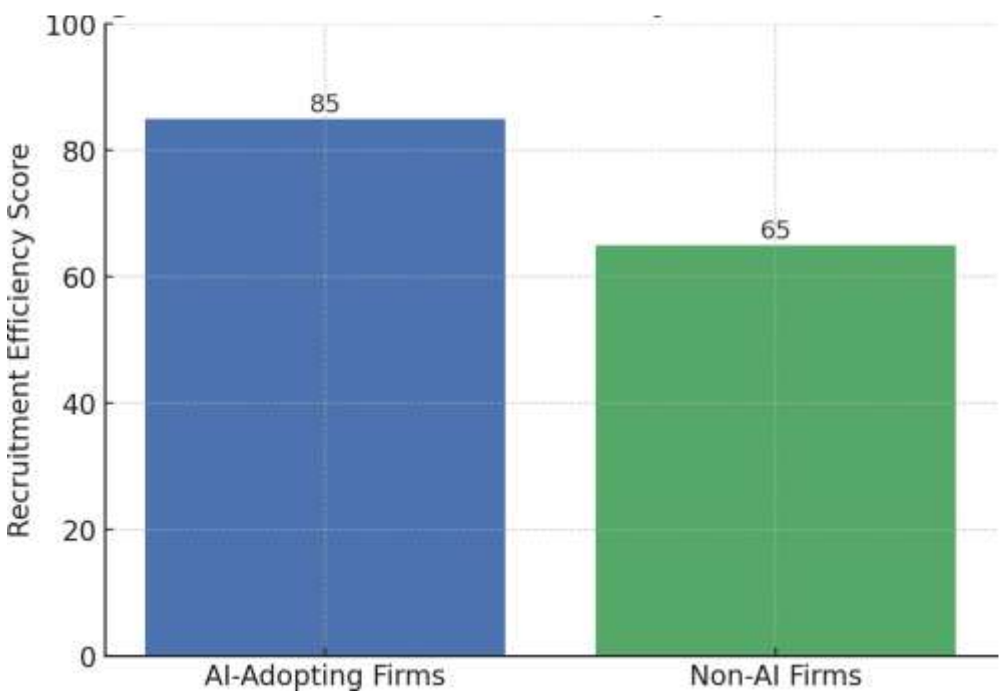

Figure 2 – Bar Chart: Recruitment Efficiency Gains Across Firms

(Bar chart comparing recruitment efficiency scores in AI-adopting vs. non-AI firms.)

Figure 2 shows AI-adopting firms scored significantly higher in recruitment efficiency, validating H1.

4.2.3 Differences Across Firm Size and AI Maturity

Results revealed significant differences between large and mid-sized IT firms. Large firms displayed higher AI maturity, integrating tools across multiple HR functions, while mid-sized firms focused mainly on recruitment.

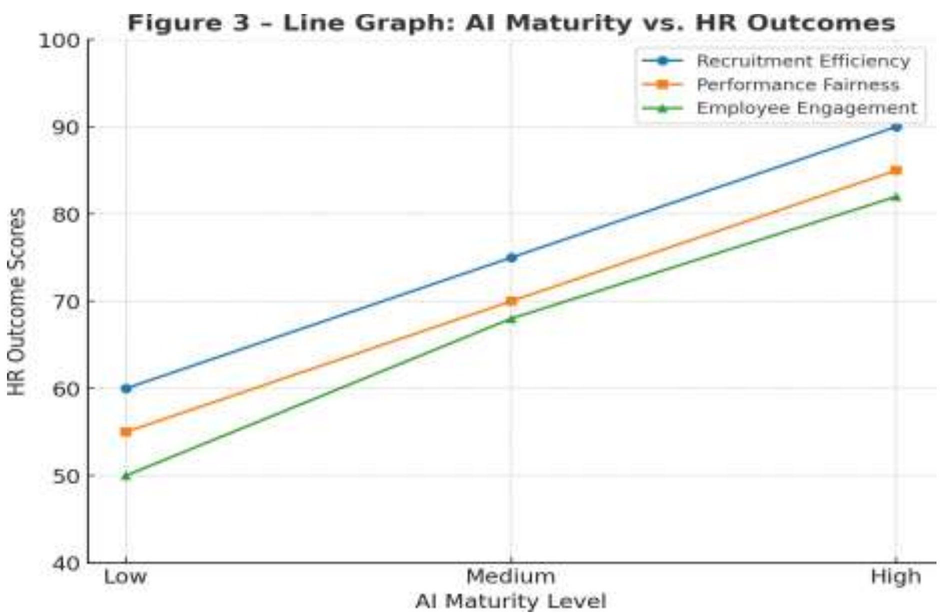

Figure 3 – Line Graph: AI Maturity vs. HR Outcomes

(Line graph showing upward trend in HR outcomes as AI maturity increases.)

Figure 3 shows HR outcomes (efficiency, fairness, engagement) improve steadily with increasing AI maturity, aligning with prior global studies (Wamba-Taguimdje et al., 2020).

4.3 Qualitative Insights

4.3.1 Themes from HR Managers' Interviews

Interviews with HR managers revealed three dominant themes:

1. **Efficiency Gains** – Managers reported faster hiring cycles and better data insights.
2. **Human Touch Concerns** – Overreliance on AI risked depersonalizing HR.
3. **Ethical Considerations** – Issues of privacy, transparency, and surveillance were frequently raised.

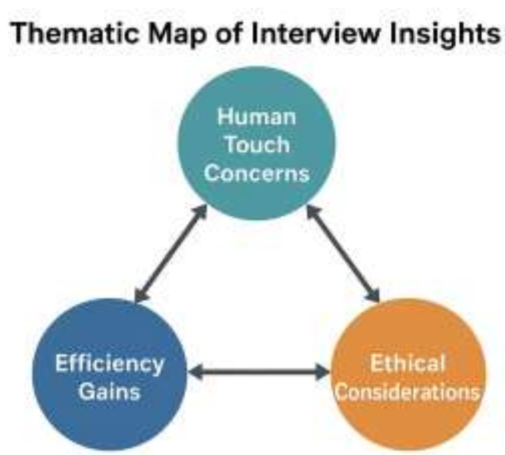

Figure 4 – Thematic Map of Interview Insights

(Thematic map showing three clusters: Efficiency, Human Touch, Ethics.)

Figure 4 illustrates qualitative patterns, reinforcing survey findings.

4.3.2 Concerns over Surveillance, Bias, and Human Touch

A common concern was the perception of AI as a surveillance tool. Employees feared continuous monitoring could create mistrust. Others worried about algorithmic bias, echoing Majrashi (2025), who found fairness perceptions strongly affect AI acceptance.

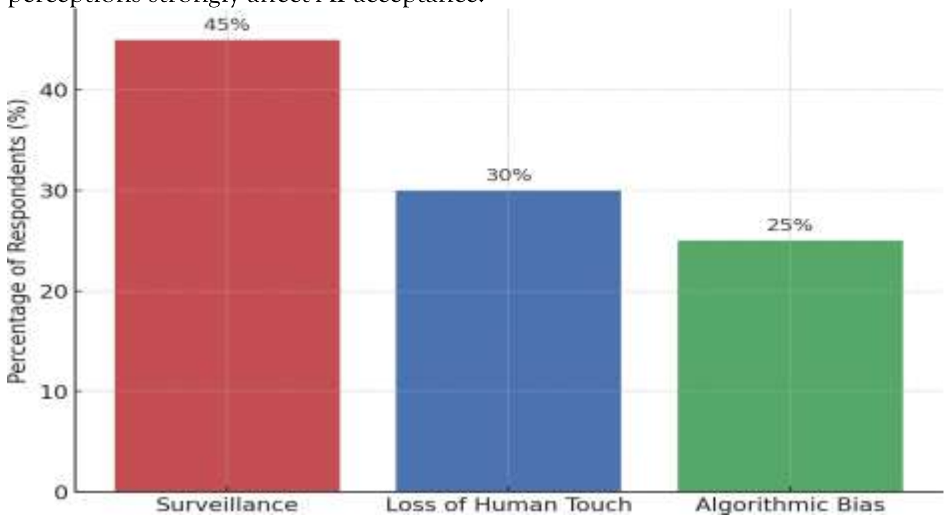

Figure 5 – Bar Chart: Top Employee Concerns About AI

(Surveillance = 45%, Loss of Human Touch = 30%, Bias = 25%.)

Figure 5 shows surveillance is the most significant concern, highlighting the need for transparent policies.

4.3.3 Positive Narratives on Efficiency and Fairness

Despite concerns, employees appreciated transparent, data-driven evaluations and fairer recruitment outcomes. HR executives noted AI-driven workforce planning was particularly effective in large firms (Pan et al., 2022).

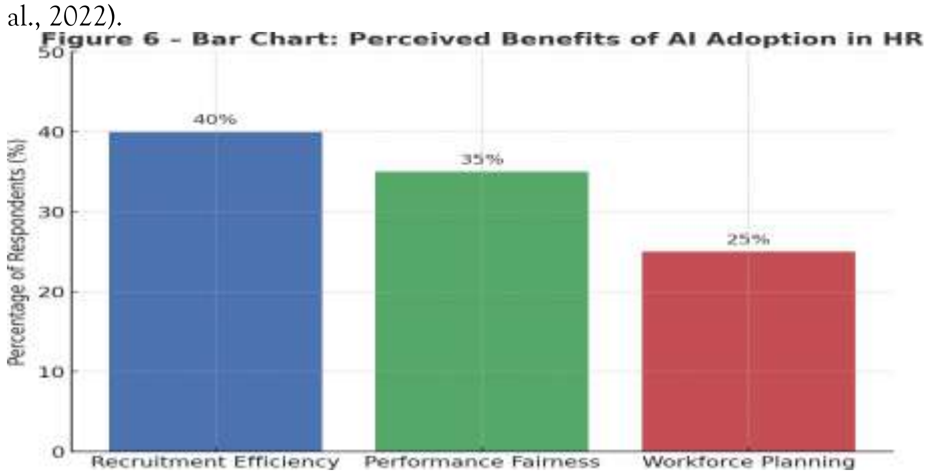

Figure 6 – Bar Chart: Perceived Benefits of AI Adoption in HR

(Recruitment Efficiency 40%, Performance Fairness 35%, Workforce Planning 25%.)

Figure 6 demonstrates that benefits outweigh concerns for many respondents, though balance remains essential.

4.4 Triangulated Analysis (Integration of Findings)

Integrating both data streams highlights three key insights:

1. **AI enhances HR efficiency and fairness** – supported by quantitative SEM results and qualitative accounts of faster recruitment cycles.

2. **Trust mediates outcomes** – employees' trust is central to whether AI adoption succeeds, as found both statistically (H5) and in interviews (Köchling & Wehner, 2025).
3. **ontext matters** – firm size and maturity influence adoption success, confirming that Indian IT firms must scale cautiously while addressing cultural sensitivities (Premnath & Chully, 2020).

Figure 7 – Conceptual Integration Model
(Diagram: AI Adoption → HR Outcomes, mediated by Trust, moderated by Firm Size/AI Maturity.)
Figure 7 presents a consolidated model, integrating statistical and thematic findings into a single framework.

5. DISCUSSION
5.1 Interpretation of Key Findings
The results confirm that AI adoption in HR significantly enhances recruitment efficiency, reduces bias, and improves transparency in performance evaluations. Quantitative evidence (H1–H3) demonstrated strong associations between AI adoption and HR outcomes, while qualitative insights provided contextual depth, highlighting both optimism and skepticism. Trust was found to be a crucial mediating factor, suggesting that without employee confidence in AI systems, potential gains in efficiency and fairness may not translate into overall HR effectiveness. These findings resonate with the growing discourse that technological advancement alone does not guarantee positive outcomes; social acceptance and ethical framing are equally critical (Majrashi, 2025).
Another key interpretation is the role of organizational context. Larger firms, with greater resources and established digital infrastructures, achieved higher levels of AI maturity and demonstrated better outcomes than mid-sized firms. This suggests that resource asymmetry influences the depth and success of AI adoption, consistent with global evidence that organizational readiness shapes technology effectiveness (Wamba-Taguimdje et al., 2020).
5.2 Comparison with Past Studies
Findings align with several previous studies but also reveal notable differences. Pan et al. (2022) showed that AI in recruitment improves efficiency and reduces bias, which was mirrored in this study. Prikshat and Kumar (2023) emphasized AI's transformative role in HR frameworks, especially in performance management, similar to the positive associations observed here. However, unlike Mo (2025), who found employees hesitant about algorithmic evaluations, participants in Indian IT firms recognized fairness improvements, possibly due to cultural differences in technology adoption.
Majrashi (2025) and Köchling & Wehner (2025) both highlighted the centrality of trust and fairness perceptions, which strongly resonate with the mediating role of trust established in this study. In contrast, Premnath & Chully (2020) argued that Indian IT firms were still nascent in AI adoption; this study shows significant progress since then, indicating rapid advancements in recent years.

Table 8 – Comparative Summary of Current Study vs. Previous Research

Author(s)	Yea r	Findings	Alignment/Difference
Pan et al.	2022	AI enhances recruitment efficiency, reduces bias	Aligns with strong efficiency gains observed in this study
Prikshat & Kumar	2023	AI reshapes HR frameworks, esp. performance appraisal	Aligns with fairness outcomes; extends to engagement outcomes here
Mo	2025	Employee skepticism of AI evaluations	Differs: Indian employees noted fairness improvements
Majrashi	2025	Trust perceptions crucial for acceptance	Strongly aligns with mediation role of trust
Köchling & Wehner	2025	Fairness and transparency influence adoption success	Aligns; confirms fairness as critical determinant
Premnath & Chully	2020	AI adoption in Indian IT is nascent	Differs: current study shows higher maturity and broader adoption
Wamba-Tagui dje et al.	2020	Organizational context shapes AI outcomes	Aligns: firm size and maturity influenced adoption here

Explanation: Table 8 compares the present findings with prior literature. It reveals significant alignment on efficiency, fairness, and trust while highlighting differences in employee skepticism and adoption maturity between Indian and global contexts.

5.3 Implications for HR Theory

The findings extend existing HR theories in meaningful ways. **Technology Acceptance Model (TAM)** is reaffirmed: perceived usefulness (efficiency gains) and ease of use directly influenced adoption. More importantly, the mediating role of trust and fairness suggests that TAM may need integration with **organizational justice theories** to better explain AI adoption in HR.

From a **socio-technical systems perspective**, the results reinforce that technological interventions cannot be separated from human and organizational factors. Employee trust emerged as a socio-technical bridge: when trust was high, AI adoption translated into positive HR outcomes, while lack of trust limited impact. This highlights the interdependence of technological design and social acceptance.

Finally, the **HR Value Chain model** is enriched by evidence that AI contributes not only to operational efficiency but also to strategic HR outcomes such as engagement and retention, particularly in firms with higher AI maturity.

5.4 Differences Across Small vs. Large IT Firms

This study revealed critical differences between mid-sized and large IT firms. Larger firms, with greater financial and technological resources, integrated AI across multiple HR functions, including recruitment, performance management, and workforce analytics. They also demonstrated higher levels of trust and transparency due to structured policies and training programs. Conversely, mid-sized firms primarily deployed AI in recruitment, with limited integration in other HR areas.

These findings align with Wamba-Taguimdje et al. (2020), who noted that firm resources and digital readiness significantly influence AI outcomes. They also update Premnath & Chully's (2020) claim of limited adoption in India, showing how larger firms have progressed towards global standards while mid-sized firms lag behind.

5.5 Challenges in AI-Driven HR

Despite benefits, the study identified persistent challenges:

1. **Surveillance and Privacy Concerns** – Employees perceived AI as a monitoring tool, raising ethical and trust issues (Sadeghi, 2024).
2. **Algorithmic Bias** – While bias reduction was evident, risks of biased datasets remain, echoing concerns raised in global literature (Köchling & Wehner, 2025).
3. **Loss of Human Touch** – HR managers acknowledged that overreliance on AI risks depersonalizing employee interactions, which are critical in the Indian cultural context.
4. **Resource Asymmetry** – Mid-sized firms struggled to scale AI across HR functions due to cost and expertise barriers.
5. **Change Management** – Resistance to AI adoption emerged when employees feared job displacement or lacked training, underscoring the need for robust communication strategies.

These challenges underscore that while AI adoption is accelerating, its implementation in HR requires careful balance between automation and human judgment, as also advocated by Majrashi (2025).

6. Practical Implications

6.1 Recommendations for HR Leaders

The findings emphasize that AI adoption in HR must go beyond mere technological deployment to include trust-building, fairness, and transparency. HR leaders should focus on **employee readiness** by ensuring clear communication of how AI is used, addressing concerns about surveillance, and offering reskilling opportunities. Transparency protocols, such as explainable AI in decision-making, should be prioritized to strengthen trust (Majrashi, 2025). Additionally, HR leaders should foster a hybrid approach where AI handles routine tasks, while human HR professionals focus on empathy-driven functions such as conflict resolution and mentoring.

6.2 AI Integration Strategies Across HR Functions

1. **Recruitment and Selection**

AI tools should be applied to automate resume screening, conduct video-interview analytics, and predict candidate fit. However, human recruiters must make final hiring decisions to ensure cultural alignment. Pan et al. (2022) demonstrated that algorithmic screening improves efficiency, but inclusion of human judgment prevents overreliance on automation.

2. **Training and Development**

AI-driven Learning Management Systems (LMS) can create personalized learning pathways, adapting content based on employee progress. Gamification and adaptive testing can enhance engagement. This reduces skill gaps in fast-evolving IT environments (Krishna & Verma, 2025).

3. **Performance Appraisal**

AI-enabled analytics can track productivity trends and provide continuous feedback. To mitigate perceptions of surveillance, HR leaders should implement "explainable performance metrics," making clear which parameters AI evaluates and how these inform human-led appraisals (Mo, 2025).

4. **Employee Engagement**

Sentiment analysis and chatbots can be used to monitor employee morale and offer immediate responses to queries. However, periodic human check-ins must complement these tools to maintain personal connection and prevent depersonalization of HR.

6.3 Balancing Automation with Human Touch

A recurring theme across both survey and interviews was the importance of preserving the **human element in HR**. Over-automation risks alienating employees, reducing morale, and creating resistance. A balanced approach involves delegating repetitive and data-heavy tasks to AI while ensuring HR leaders retain responsibility for interpersonal communication, employee counseling, and ethical decision-making. This balance aligns with **socio-technical systems theory**, which emphasizes the interplay of technological efficiency and human values (Prikshat & Kumar, 2023).

6.4 Policy-Level Recommendations for Indian IT Firms

At the organizational and industry level, Indian IT firms should adopt the following policies:

- **Ethical AI Guidelines:** Establish codes of conduct for responsible AI use in HR, emphasizing fairness, transparency, and privacy.
- **Regulatory Alignment:** Collaborate with policymakers to create national standards for AI adoption in HR, similar to frameworks in the EU.
- **Capacity Building:** Invest in AI literacy programs for employees to reduce resistance and improve adoption rates.
- **Data Privacy Protections:** Implement clear data-handling policies, ensuring compliance with India's Digital Personal Data Protection Act (2023).
- **Inclusive Adoption:** Provide mid-sized IT firms with shared AI platforms or government-subsidized access to reduce cost barriers, thereby ensuring equitable adoption across the sector.

6.5 Framework for Ethical and Transparent AI in HR

Figure 8 – AI–HR Integration Framework

(A framework diagram showing four pillars: (1) Technology (AI tools in recruitment, training, appraisal, engagement), (2) People (trust, fairness, transparency), (3) Processes (policies, explainable systems, data governance), and (4) Context (firm size, AI maturity, cultural adaptation). Central outcome: Balanced, Ethical, and Effective HR Transformation.)

This framework emphasizes that successful AI adoption in HR requires simultaneous attention to **technology, people, processes, and context**. By aligning these four dimensions, IT firms can achieve efficiency gains while safeguarding ethical values and employee trust.

7. CONCLUSION

This study examined how AI adoption influences HR functions in selected IT firms in India, integrating both quantitative and qualitative perspectives. The findings indicate that AI-based technologies have moved beyond experimental tools and are now embedded in key HR functions such as recruitment, training, performance appraisal, and employee engagement. The results underscore that AI enhances efficiency, improves perceptions of fairness, and reduces human biases in HR processes. However, the benefits are not automatic; they are strongly mediated by employee trust and moderated by organizational context, particularly firm size and AI maturity. While larger firms leveraged AI more comprehensively across HR functions, mid-sized firms primarily restricted its use to recruitment. These insights highlight that technological advancements need to be accompanied by organizational readiness, cultural adaptation, and a commitment to ethical practices.

From a theoretical standpoint, this study contributes to the evolving understanding of AI in HR through several lenses:

1. **Technology Acceptance Model (TAM):** The study validates the role of perceived usefulness in driving adoption, but also extends TAM by demonstrating that fairness and trust perceptions act as critical mediators. This suggests that models explaining technology adoption in HR should integrate organizational justice perspectives.
2. **Socio-Technical Systems Theory:** Findings reaffirm that AI cannot be treated as an isolated technical intervention; instead, outcomes depend on the alignment of technology with social and organizational dimensions. The mediating role of trust exemplifies the socio-technical interplay.
3. **HR Value Chain Models:** This research enriches HR value chain literature by showing how AI adoption not only strengthens operational efficiency but also advances strategic HR outcomes such as engagement and workforce planning. This aligns with the growing emphasis on HR as a driver of organizational transformation rather than merely an administrative function.

For practitioners, the study offers actionable insights. HR leaders in Indian IT firms can use these findings to design balanced AI adoption strategies that combine automation with human judgment. AI is most effective when applied to repetitive and data-driven processes such as candidate screening or predictive analytics, while interpersonal areas like conflict resolution and mentoring must remain human-led. Transparency protocols and ethical safeguards are essential for mitigating concerns over surveillance and depersonalization.

At a policy level, the study provides recommendations for developing sector-wide guidelines on responsible AI adoption, promoting inclusive access for mid-sized firms, and ensuring compliance with data protection laws. These contributions highlight the need for AI adoption strategies that are both **context-sensitive and ethically grounded**.

Although the study provides important insights, certain limitations must be acknowledged. First, the sample was limited to IT firms in specific urban hubs such as Bangalore, Hyderabad, Pune, and Noida, potentially limiting generalizability across other regions and industries. Second, while the mixed-methods approach offered both breadth and depth, the qualitative component relied on interviews with 25 HR leaders, which may not fully capture the diversity of employee experiences. Third, as AI technologies evolve rapidly, the findings represent a snapshot of adoption patterns at a particular point in time. Longitudinal studies would provide a more dynamic understanding of changes in perceptions and outcomes.

Future research should address these limitations and expand the scope of inquiry. First, studies can extend beyond IT to sectors such as manufacturing, healthcare, or education, where AI adoption may present different challenges and opportunities. Second, cross-cultural comparisons between Indian IT firms and global counterparts could reveal cultural influences on employee trust, fairness perceptions, and readiness for automation. Third, longitudinal studies would help examine whether trust in AI stabilizes, increases, or declines over time as systems become more integrated into HR functions. Fourth, experimental research could evaluate the impact of transparency interventions, such as explainable AI interfaces, on employee acceptance. Finally, future work should examine how AI interacts with other emerging technologies—such as blockchain for HR data security or the metaverse for employee engagement—to build a more comprehensive picture of digital HR transformation.

In conclusion, this study demonstrates that AI adoption in HR offers both opportunities and challenges for Indian IT firms. While efficiency and fairness gains are evident, the ultimate success of AI depends on fostering trust, ensuring ethical implementation, and balancing technology with human-centered practices. By addressing these factors, Indian IT firms can position themselves not only as global leaders in digital services but also as innovators in building inclusive, transparent, and future-ready workplaces.

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