

**Artificial Intelligence, HR Analytics and the Changing Role of HR Managers:  
An Empirical Study of Organisations in Delhi NCR**

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**Abstract**

Artificial Intelligence (AI), machine learning, people analytics and related digital technologies are increasingly influencing the structure and delivery of contemporary human resource management (HRM). The implications extend beyond the automation of routine activities because these technologies can alter how HR managers recruit employees, analyse workforce information, monitor performance, identify talent requirements and contribute to organisational decision-making. This paper examines the changing role of HR managers in the context of AI and HR analytics, with particular reference to organisations operating in Delhi National Capital Region (NCR). The paper conceptualises AI adoption and HR analytics adoption as major technological drivers, while HR manager digital competency and organisational readiness are considered important intervening factors. The changing role of HR managers is examined through dimensions such as administrative responsibility, data-driven decision-making, strategic contribution, employee experience management, change management and ethical technology governance. The study proposes a quantitative empirical design involving HR managers and HR professionals from Delhi, Gurugram, Noida, Greater Noida, Ghaziabad and Faridabad. It further proposes examining whether AI and analytics adoption is associated with reduced routine workload and increased strategic contribution.

**Keywords:** Artificial intelligence, HR analytics, people analytics, HR managers, digital HRM, automation, augmentation, Delhi NCR, strategic HRM.

**1. Introduction**

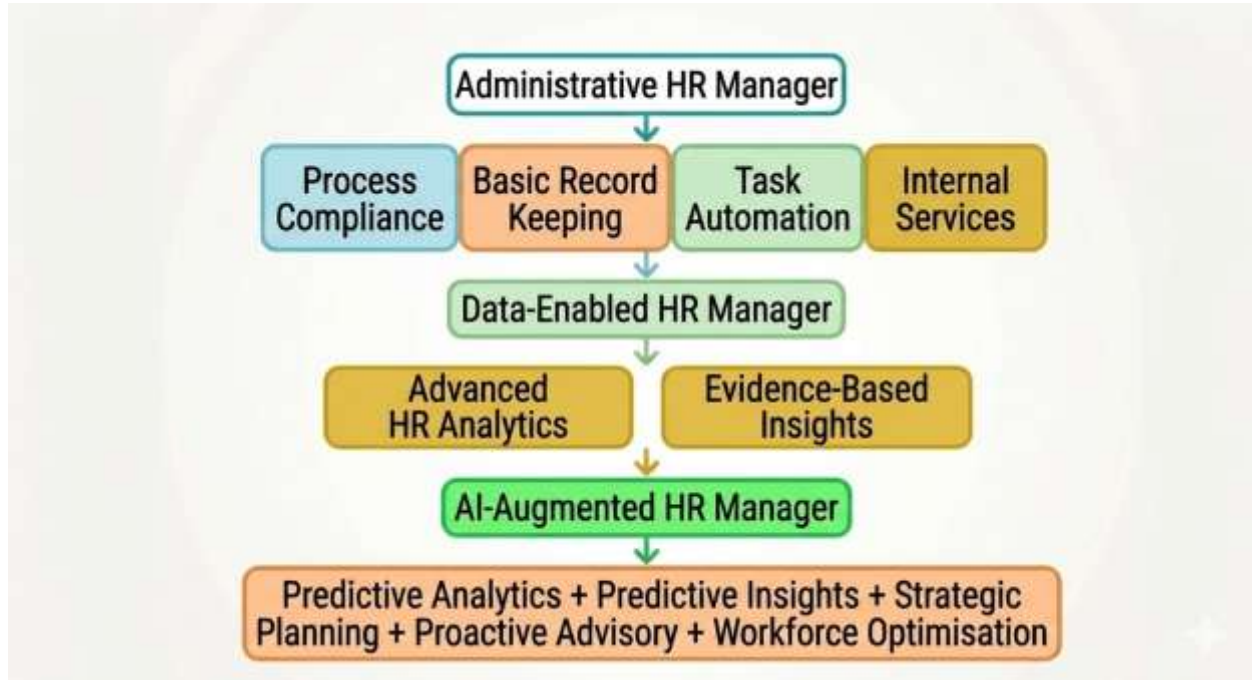
Human resource management has traditionally combined administrative, operational and strategic responsibilities. HR managers have been responsible for recruitment, employee records, attendance, payroll coordination, training, performance management, employee relations and compliance. Although these functions remain necessary, technological developments have progressively changed how they are performed.

The emergence of Artificial Intelligence and HR analytics represents a further stage of this transformation. AI can support activities such as candidate screening, conversational HR services, workforce forecasting and pattern recognition, while HR analytics can convert employee-related data into information for managerial decision-making. Tursunbayeva, Di Lauro and Pagliari (2018) note that people analytics has developed alongside several related forms of data-driven workforce management, although the evidence concerning organisational value and ethical considerations remains uneven. ([ScienceDirect](#))

The significance of these developments lies in their potential to change the role rather than merely the tools of HR managers. A manager who previously spent substantial time preparing reports or

processing employee information may increasingly be expected to interpret dashboards, evaluate algorithmic recommendations, advise management and manage employee concerns arising from digital systems.

This transformation can be expressed as:



The transition, however, is neither automatic nor universal. AI implementation can encounter problems related to data quality, employee acceptance, privacy, fairness, organisational readiness and managerial capability. Tambe, Cappelli and Yakubovich identify complexity in HR phenomena, limitations associated with data, ethical and legal concerns, and employee reactions to algorithmic management as significant challenges for AI in HRM. (HubSpot)

## 2. Background of the Study

### 2.1 From Traditional HRM to Intelligent HRM

Traditional HRM was primarily process-oriented. HR managers were expected to ensure that established procedures were completed accurately and consistently. Digital HR initially supported these activities through HRIS and electronic records.

The subsequent development of HR analytics introduced a stronger evidence-based orientation. Instead of merely reporting employee numbers, HR departments could examine patterns relating to turnover, absenteeism, recruitment, performance and workforce composition.

AI extends this development by introducing technologies capable of classification, prediction, recommendation, natural-language interaction and automated decision support.

| Stage                | Primary HR orientation         | Typical HR role             |
|----------------------|--------------------------------|-----------------------------|
| Traditional HR       | Administration                 | Transaction processor       |
| Digital HR           | Process digitisation           | Technology user             |
| Analytics-enabled HR | Evidence-based decision-making | Data interpreter            |
| AI-enabled HR        | Prediction and augmentation    | AI-enabled decision partner |
| Strategic HR         | Organisational value           | Strategic HR partner        |

### 3. Artificial Intelligence in HRM

AI refers broadly to computational systems capable of performing tasks associated with human cognitive functions, including classification, prediction, pattern recognition and language processing.

In HRM, applications may include:

- AI-supported recruitment;
- candidate matching;
- automated CV screening;
- HR chatbots;
- employee query management;
- workforce forecasting;
- attrition-risk analysis;
- skills analysis;
- personalised learning recommendations;
- performance-support systems.

However, AI adoption should not be equated with complete automation. Raisch and Krakowski (2021) distinguish between automation, in which machines take over tasks, and augmentation, in which humans work together with machines. Their analysis suggests that organisations need to consider the interaction between the two rather than assuming that one will simply replace the other. ([DOI.org](https://doi.org/10.1016/j.chbs.2021.100888))

### 4. HR Analytics and People Analytics

HR analytics involves the systematic use of workforce data to generate information that supports HR and organisational decisions. People analytics is closely related but may encompass broader organisational and workforce data.

Tursunbayeva et al. (2018) found that people analytics has developed across HRM, business analytics and information-management disciplines. Their review also identified gaps in training and limited consideration of ethical issues. ([ScienceDirect](https://www.sciencedirect.com/science/article/pii/S0950080418300091))

#### Major forms of HR analytics

| Type         | Main question       | HR example                             |
|--------------|---------------------|----------------------------------------|
| Descriptive  | What happened?      | Employee turnover rate                 |
| Diagnostic   | Why did it happen?  | Reasons for absenteeism                |
| Predictive   | What may happen?    | Attrition prediction                   |
| Prescriptive | What could be done? | Retention intervention recommendations |

The development of analytics therefore changes the HR manager's responsibility from **reporting information to interpreting information and converting it into organisational action.**

### 5. Changing Role of HR Managers

#### 5.1 From Administrator to Strategic Partner

The most important transformation concerns the allocation of HR managers' time. Automation can reduce involvement in repetitive administrative activities and potentially create greater capacity for workforce planning, organisational development and strategic advisory work.

### **5.2 HR Manager as Data Interpreter**

HR managers increasingly need to understand dashboards, trends, correlations and predictive outputs. They do not necessarily need to become specialist data scientists, but they need sufficient analytical literacy to question data quality, understand limitations and interpret findings responsibly.

### **5.3 HR Manager as Technology Facilitator**

The HR manager increasingly acts as a bridge between technology providers, IT departments, senior management and employees. This requires understanding both technological capabilities and organisational requirements.

### **5.4 HR Manager as Change Manager**

AI implementation can alter job roles, workflows and decision-making authority. HR managers therefore have an important role in communicating change, managing resistance and supporting employee adaptation.

### **5.5 HR Manager as Ethical Technology Manager**

Algorithmic HR systems can generate concerns regarding fairness, transparency, privacy and employee surveillance. Research on the ethics of people analytics emphasises the need to address such risks systematically. ([UT Research Info](#))

## **6. Research Gap**

Although AI and people analytics have attracted increasing academic and managerial attention, several gaps remain.

First, much of the literature discusses AI applications individually rather than examining their combined influence on the role of HR managers.

Second, technology adoption does not necessarily mean effective technology utilisation. HR manager competency and organisational readiness may determine whether technology creates meaningful organisational value.

Third, there is limited context-specific empirical investigation of how AI and analytics are transforming HR managerial responsibilities across different organisational sectors within Delhi NCR.

Fourth, AI transformation involves both automation and augmentation. Therefore, examining only whether HR jobs are automated may provide an incomplete understanding of the changing managerial role.

This study seeks to address these gaps through an empirical framework focused on organisations in Delhi NCR.

## **7. Objectives of the Study**

- ❖ To examine the extent of AI adoption in HR operations in organisations in Delhi NCR.
- ❖ To assess the adoption of HR analytics and people analytics practices.
- ❖ To examine the changing operational responsibilities of HR managers.
- ❖ To assess the changing competencies required by HR managers in AI-enabled workplaces.
- ❖ To examine the relationship between AI adoption and the strategic contribution of HR managers.
- ❖ To analyse the relationship between HR analytics adoption and data-driven HR decision-making.

- ❖ To examine the challenges associated with AI and analytics adoption.
- ❖ To develop recommendations for responsible and effective AI-enabled HR transformation.

## **8. Research Questions**

1. To what extent is AI being adopted in HR functions in Delhi NCR?
2. What HR activities are most affected by AI and analytics?
3. How has HR analytics changed HR managers' decision-making responsibilities?
4. What new competencies are required by HR managers?
5. Does AI adoption reduce routine administrative workload?
6. Does AI adoption increase the strategic contribution of HR managers?
7. What organisational factors influence successful AI adoption?
8. What ethical and operational challenges do HR managers face?

## **9. Research Hypotheses**

**H1:** AI adoption has a significant positive relationship with the strategic contribution of HR managers.

**H2:** HR analytics adoption has a significant positive relationship with data-driven HR decision-making.

**H3:** AI adoption has a significant negative relationship with routine administrative workload.

**H4:** HR manager digital competency has a significant positive relationship with effective AI utilisation.

**H5:** HR manager analytical competency has a significant positive relationship with HR analytics utilisation.

**H6:** Organisational readiness has a significant positive relationship with effective AI adoption.

**H7:** AI adoption has a significant positive relationship with employee-service responsiveness.

**H8:** Responsible AI governance is significantly associated with employee trust in AI-enabled HR processes.

## **10. Conceptual Framework**

The proposed conceptual framework is:

AI Adoption



HR Analytics Adoption



Automation + Decision Support + Prediction



HR Manager Digital & Analytical Competency



Transformation of HR Manager Role



Reduced Routine Work + Improved Decision Support



Strategic HR Contribution

Two contextual factors are proposed to influence this relationship:

## **11. Research Methodology**

### 11.1 Research Design

A **descriptive and analytical quantitative research design** is appropriate. The descriptive component can assess the current level of AI and analytics adoption, while the analytical component can examine relationships among AI adoption, competencies, role transformation and strategic contribution.

### 11.2 Study Area

The study focuses on Delhi NCR, including:

- Delhi
- Gurugram
- Noida
- Greater Noida
- Ghaziabad
- Faridabad

### 11.3 Target Population

The target population may include:

- HR managers;
- HR executives;
- HR business partners;
- HR operations professionals;
- senior HR professionals;
- HR analytics professionals;
- HR technology professionals.

### 11.4 Illustrative Sample

A sample of **300 respondents** may be proposed for the empirical study, subject to actual accessibility and sampling procedures.

| Location      | Illustrative respondents |
|---------------|--------------------------|
| Delhi         | 70                       |
| Gurugram      | 60                       |
| Noida         | 60                       |
| Greater Noida | 30                       |
| Ghaziabad     | 40                       |
| Faridabad     | 40                       |
| <b>Total</b>  | <b>300</b>               |

**Important:** These are proposed illustrative values, not research findings. Actual values should be replaced after data collection.

## 12. Research Instrument

A structured questionnaire can be divided into the following sections:

| Section | Variables             |
|---------|-----------------------|
| A       | Demographic profile   |
| B       | AI adoption           |
| C       | HR analytics adoption |

|   |                              |
|---|------------------------------|
| D | Automation                   |
| E | Digital competency           |
| F | Analytical competency        |
| G | Organisational readiness     |
| H | Changing HR role             |
| I | Strategic HR contribution    |
| J | Employee experience          |
| K | Ethical and privacy concerns |
| L | Future expectations          |

A five-point Likert scale can be used for attitudinal statements:

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

### 13. Data Analysis

The proposed analysis may include:

- Frequency;
- Percentage;
- Mean;
- Standard deviation;
- Cronbach's alpha;
- Correlation;
- t-test;
- ANOVA;
- Factor analysis;
- Multiple regression.

Where the final sample and measurement model justify it, **Structural Equation Modelling (SEM)** may also be used.

An illustrative regression equation is:

$$\text{SCR} = \beta_0 + \beta_1\text{AI} + \beta_2\text{HA} + \beta_3\text{DC} + \beta_4\text{OR} + \varepsilon$$

Where:

- **SCR** = Strategic contribution of HR managers
- **AI** = AI adoption
- **HA** = HR analytics adoption
- **DC** = Digital competency
- **OR** = Organisational readiness
- $\varepsilon$  = Error term

Actual coefficients, significance levels and model-fit statistics should only be reported after analysing genuine survey data.

### 14. Changing Competencies of HR Managers

AI-enabled HRM requires a broader competency portfolio.

| <b>Traditional competency</b> | <b>Emerging competency</b>         |
|-------------------------------|------------------------------------|
| Administrative knowledge      | Digital HR knowledge               |
| Record management             | Data management                    |
| Routine reporting             | Data interpretation                |
| Manual recruitment            | AI-supported recruitment           |
| Conventional communication    | Digital communication              |
| Procedural compliance         | Technology governance              |
| Basic HR reporting            | HR analytics                       |
| Traditional problem-solving   | Technology-enabled problem-solving |
| Employee administration       | Employee experience management     |
| Change implementation         | Digital change management          |

The central competency shift is therefore from **process execution** towards **technology-supported judgement and strategic interpretation**.

## **15. Challenges of AI and HR Analytics**

### **15.1 Data Quality**

AI systems depend on data. Incomplete, inaccurate or inconsistent HR data can undermine analytical outputs.

### **15.2 Algorithmic Bias**

AI systems may reproduce or amplify patterns embedded in historical data. This is particularly important in recruitment and performance-related applications.

### **15.3 Employee Trust**

Employees may perceive algorithmic monitoring or analytics as intrusive if the purpose and use of data are unclear.

### **15.4 Privacy and Security**

HR data can contain sensitive employment information. Strong governance and cybersecurity practices are therefore essential.

### **15.5 Skill Gaps**

HR managers may understand HR processes but lack sufficient analytical or technological expertise to evaluate AI outputs.

### **15.6 Over-Automation**

Excessive dependence on automated systems can reduce human judgement in situations requiring contextual understanding. The automation–augmentation literature suggests that organisations need to consider both technological automation and human-machine collaboration. ([DOI.org](https://doi.org/))

## **16. Discussion**

AI and HR analytics have the potential to transform HR managers' work in two complementary ways.

First, **automation** can reduce repetitive activities. Examples include routine employee queries, document classification, basic scheduling and certain reporting processes.

Second, **augmentation** can improve human decision-making by providing HR managers with information, predictions and recommendations. The distinction is important because HR management frequently involves ambiguity, interpersonal relationships and ethical judgement. Tambe et al. highlight the difficulty of applying conventional data-science assumptions to HR because employee behaviour is complex and HR data may be constrained. (HubSpot) This suggests that HR managers should not accept algorithmic outputs uncritically.

### 17. Managerial Implications

#### For HR Managers

HR professionals should develop competencies in data interpretation, AI literacy, digital communication and technology-enabled decision-making.

#### For Senior Management

AI adoption should be evaluated according to measurable improvements in HR outcomes rather than technology adoption alone.

#### For HR Departments

Departments should identify activities that are suitable for automation while retaining human oversight for high-impact employee decisions.

#### For Employees

Organisations should clearly communicate how employee data are collected, analysed and used.

#### For HR Technology Providers

Technology providers should prioritise explainability, privacy, interoperability, usability and mechanisms for human review.

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### 18. Proposed Transformation Framework

The study proposes the following framework:

AI & Digital Infrastructure



HR Data Integration



HR Analytics



Automation & AI Decision Support



HR Manager Digital Competency



Role Transformation



Strategic HR Contribution



Organisational Value

The framework is moderated by:

**Organisational Readiness + Ethical Governance + Employee Trust**

This framework reflects the view that AI implementation should be accompanied by human capability development and responsible governance.

### **19. Conclusion**

Artificial intelligence and HR analytics are changing the substance of HR managerial work. Their influence extends beyond automating administrative tasks because they affect recruitment, workforce analysis, employee services, performance management and managerial decision-making. The transformation does not necessarily imply the disappearance of HR managers. Instead, it is more appropriately understood as a shift from **administrative execution towards technology-enabled judgement and strategic contribution**. Automation can remove selected repetitive tasks, while augmentation can strengthen the capacity of HR managers to interpret workforce information and support organisational decisions.

For organisations in Delhi NCR, the successful adoption of AI and HR analytics will depend on more than investment in technology. Organisational readiness, data quality, HR manager competency, employee trust, privacy and ethical governance will be equally important.

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