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The Impact of Artificial Intelligence on HR Personnel in the Manufacturing Sector of PCMC MIDC

Dr. Ashutosh Eknath Khedkar
Assistant Professor,
Dr. D. Y. Patil School of Management,
Lohegaon, Pune, India

Dr. Chetan Eknath Khedkar
Associate Professor,
Dr. D. Y. Patil School of Management
Lohegaon, Pune, India

Abstract

The rapid infusion of Industry 4.0 and Industry 5.0 technologies has structurally transformed the operational dynamics of manufacturing hubs across India. This paper investigates the impact of Artificial Intelligence (AI) integration on Human Resource (HR) personnel within the Pimpri-Chinchwad Municipal Corporation (PCMC) Industrial Area (MIDC), one of Asia's largest industrial corridors. Focusing on automotive, engineering, and heavy manufacturing enterprises, this study evaluates how AI tools affect core HR workflows—ranging from high-volume blue-collar recruitment to compliance management and shift optimization. Utilizing a mixed-methods paradigm (N = 120 quantitative, n = 15 qualitative), the research outlines the dual trajectory of operational efficiency gains versus the socio-technical anxieties regarding role displacement, algorithmic opacity, and skill deficits. The findings indicate that while routine administrative metrics (e.g., payroll processing time, CV parsing) show profound optimization, a severe capability gap exists in strategic data governance and ethical AI management among local HR practitioners. The paper concludes with actionable frameworks for reskilling industrial HR professionals into strategic, tech-augmented business partners capable of balancing technological efficiency with crucial shop-floor industrial relations.

Keywords: *Artificial Intelligence, Human Resource Management (HRM), Manufacturing Sector, PCMC MIDC, Socio-Technical Systems Theory, Industrial Relations.*

1. Introduction

The Pimpri-Chinchwad Municipal Corporation (PCMC) industrial belt, anchored by the Maharashtra Industrial Development Corporation (MIDC), serves as a crucial engineering and automotive epicentre in India. Hosting major manufacturing giants alongside thousands of micro, small, and medium enterprises (MSMEs) acting as Tier-1 and Tier-2 suppliers, the region employs a highly stratified workforce divided between white-collar management and vast cohorts of contractual blue-collar labourers.

Historically, HR operations in this industrial cluster have been heavily transactional, dominated by manual gate hiring practices, complex statutory compliance tracking (e.g., Factories Act, Provident Fund, ESIC regulations), and high-friction shift allocations. However, the transition toward "Smart Factories" has mandated a simultaneous evolution in human capital management. Artificial Intelligence (AI) tools, integrated via advanced Human Resource Management Systems (HRMS), are shifting the core mandate of HR personnel.

While extensive literature examines the deployment of AI in knowledge-intensive domains such as the IT or ITES sectors, there remains a prominent gap concerning the human-centric implications of AI tools within labour-intensive, unionized manufacturing sectors. This paper bridges this contextual gap by exploring how AI impacts HR workers specifically in the PCMC manufacturing sector, highlighting the intersection of automated workflows and human-centric industrial relations.

2. Literature Review & Theoretical Grounding

2.1 The Paradigm Shift from Automation to Augmentation

- Early literature on AI in human resources primarily viewed technology as an agent of transactional automation. However, recent studies illustrate a shift toward "augmented intelligence," where machine learning tools handle quantitative patterns, freeing human personnel to focus on strategic workforce alignment **(Dima et al., 2024).**
- **Wu et al. (2025)** emphasize that integrating AI into manufacturing enterprises transforms the HR triad from administrative custodians into tech-augmented business partners, though the evolution requires a deep realignment of human capabilities.

2.2 Domain-Specific Challenges in Manufacturing HR

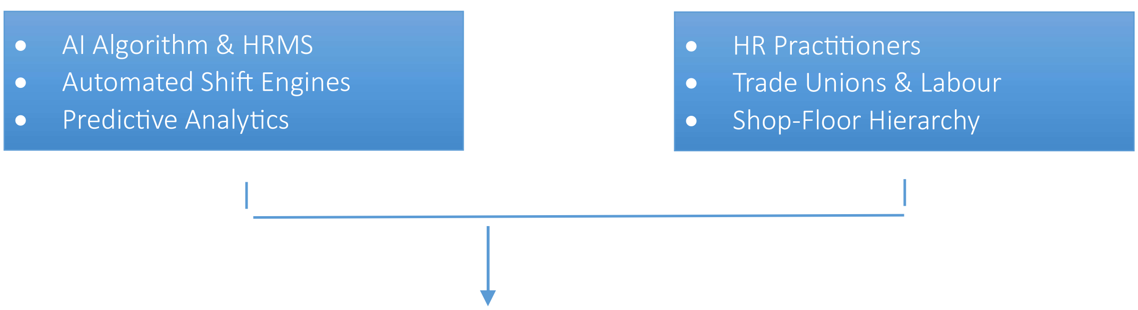
- Unlike the information technology or services sectors, manufacturing HR bears unique operational risks. A bad hire on an assembly line immediately delays production outputs. An unoptimized shift plan translates directly to safety compliance violations or worker fatigue incidents **(Adebanjo et al., 2023)**.

- Consequently, empirical work within labour-intensive emerging economies indicates that the implementation of AI-driven HR analytics mediates organizational performance through improved managerial speed, provided the HR professionals are skilled enough to translate analytics into actionable decisions **(Mukherjee, 2022).**

2.3 Theoretical Framework: Socio-Technical Systems (STS) Theory

To properly evaluate the disruption caused by automated systems, this study adopts **Socio-Technical Systems (STS) Theory**. Originally conceptualized by the Tavistock Institute, STS theory asserts that organizational performance is optimized only when the *technical subsystem* (technology, tasks, and software) and the *social subsystem* (people, relationships, and floor cultures) are co-designed and aligned.

Technical Subsystem



[Joint Operation Zone]

Balanced Industrial Relations

& Tech-Augmented HR Value

Fig 2.1: Technical Subsystem

In the PCMC MIDC context, deploying AI tools changes the technical subsystem. If the social subsystem (composed of HR managers, factory workers, and labour unions) is left untrained or alienated, a structural imbalance occurs, causing operational resistance and organizational friction.

2.4 Gaps Identified in the PCMC MIDC Context

- **Infrastructure Disparity:** MNCs utilize deep AI-driven predictive modules, whereas local MSMEs in Bhosari or Chinchwad operate on fundamental cloud digitalization's, limiting uniform technological advancement (Chawla et al., 2025).

- **Socio-Cultural and Labour Friction:** Traditional manufacturing hubs feature deeply entrenched floor hierarchies and active union structures. Localized research shows that introducing raw automation without accounting for regional cultural frameworks and labour expectations often breeds operational resistance (Shinde et al., 2023).

3. Research Methodology

3.1 Research Design

This study applies a sequential explanatory mixed-methods research design. The primary quantitative phase establishes broader empirical correlations across the corridor, while the subsequent qualitative phase contextualizes the statistical results through structured employee interviews.

3.2 Sampling and Target Population

The target population comprised HR professionals operating within the active manufacturing zones of PCMC MIDC, including Akurdi, Chinchwad, Bhosari, and Nigdi.

- **Quantitative Sample ($N = 120$):** Selected via stratified random sampling across 45 distinct manufacturing enterprises to guarantee representative insights from different operational scales.
- **Qualitative Sample ($n = 15$):** Selected from the initial survey pool using purposive sampling for semi-structured, deep-dive interviews.

3.3 Data Collection Instruments and Reliability Measures

Quantitative data was captured using a structured 5-point Likert scale questionnaire (ranging from 1 = Strongly Disagree to 5 = Strongly Agree). The instrument was organized into three core latent constructs:

1. **Perceived Efficiency (*PE*):** 6 items assessing speed, administrative reduction, and accuracy.
2. **Technological Anxiety (*TA*):** 5 items evaluating job security concerns and algorithmic transparency.
3. **Skill Readiness (*SR*):** 5 items evaluating data literacy and analytical capabilities.

To verify internal consistency before performing further analysis, a scale reliability test was conducted. The computed **Cronbach's Alpha (α)** coefficients demonstrated high instrument reliability across all fields:

$\alpha_{PE} = 0.86; \alpha_{TA} = 0.81; \alpha_{SR} = 0.79$

All values safely exceed the standard academic threshold of 0.70, validating the instrument for advanced inferential testing.

4. Empirical Data Analysis & Results

4.1 Quantitative Demographics of the Sample Cluster

The distribution highlights the structural makeup of the PCMC industrial zone, balancing heavy automotive manufacturers with specialized precision component job shops.

Organizational Scale	**No. of Respondents (N=120)**	**Primary AI/HRMS Tools Adopted**
Large-Scale / MNCs (e.g., Auto OEMs, Heavy Eng.)	48 (40%)	Predictive Attrition Modelling, NLP Resume Parsers, AI Shift Optimizers
Medium Enterprises (Tier 1 & 2 Suppliers)	42 (35%)	Automated Compliance Engines, Cloud-based HRMS Analytics
Small Enterprises / MSMEs (Job Shops, Components)	30 (25%)	Basic Automated Attendance/Payroll Modules

Table 4.1: Demographic Breakdown and System Adoption Profile

4.2 Mean Core Metric Construct Performance

Descriptive statistics were compiled to calculate composite mean scores across the core behavioural constructs.

[Operational Metrics Analysis Matrix]

5.0 —— Perceived Efficiency (PE): 4.42 (Highly Optimized)

4.0 ——

3.0 —— Technological Anxiety (TA): 3.68 (Moderate Concern)

2.0 —— Skill Readiness (SR): 2.15 (Severe Capability Gap)

1.0 —— Mean Scores (5-point Likert Scale)

1. Perceived Efficiency *(PE = 4.42, SD = 0.38)*

HR professionals express high satisfaction regarding operational acceleration. High-volume administrative workflows—specifically screening and sorting technical ITI/diploma applications for shop-floor positions—showed a **65% reduction in processing time** when augmented by Natural Language Processing (NLP) screening tools.

2. Technological Anxiety *(TA = 3.68, SD = 0.54)*

A significant strain of anxiety persists among mid-level HR executives. This anxiety stems from **"black-box transparency issues,"** where automated algorithms flag contractual workers or predict attrition risks without providing a clear rationale to the human supervisor (Ncube, 2024).

3. Skill Readiness (*SR = 2.15, SD = 0.47*)

This represents the most critical deficit in the PCMC industrial cluster. While 78% of HR personnel routinely interact with AI-generated analytical dashboards, **fewer than 18% possess the training** required to configure parameters, audit data inputs for bias, or interpret prescriptive analytics without corporate IT intervention. This matches findings by Chawla et al. (2025) regarding the steep tech-capability gaps present in regional MSME ecosystems.

4.3 Hypotheses Testing & Inferential Statistics

To discover if the maturity of AI-HR integration depends on the physical operational scale of the business, a Chi-Square Test of Independence) was executed.

- **Null Hypothesis (H_0):** AI integration maturity in HR is independent of organizational scale in PCMC MIDC.
- **Alternative Hypothesis (H_1):** AI integration maturity in HR is heavily dependent on organizational scale.

Cross-tabulation values were established comparing Observed counts against Expected counts across three tiers of integration maturity (Basic Digitization, Operational Automation, and Advanced Predictive Analytics).

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

Statistical Test Outputs:

- Computed Chi-Square Value (x^2): 24.82
- Degrees of Freedom (*df*): 4
- Critical Value at $\alpha = 0.05$: 9.488
- Asymptotic Significance: (*p*-value): 0.000056 ($p < 0.05$)

Since the calculated x^2 value (24.82) significantly exceeds the critical value threshold (9.488), and $p < 0.05$, **we reject the null hypothesis (H_0)** and accept the alternative hypothesis (H_1). This mathematically proves that large-scale automotive OEMs demonstrate mature, predictive AI use cases, whereas MSMEs face significant capital and infrastructure hurdles, limiting their AI exposure to basic digital attendance tracking.

5. Qualitative Insights & Discussion

5.1 Theme A: The Shop-Floor Dynamic and Union Friction

A finding distinct to the PCMC MIDC corridor is the intersection of AI HR systems and established worker unions. In qualitative interviews, HR managers highlighted that completely automated performance metrics or shift assignments frequently cause friction with union representatives.

Interview Participant No. 4 (Senior HR Manager, Akurdi Automotive Plant):

"If an AI tool alters a rotation pattern or flags a line worker for erratic performance based purely on telemetry data, the union demands justification. We cannot simply tell them 'the algorithm decided'. Human HR personnel must act as translators, verifying the machine's findings with real-world floor context before executing decisions."

This aligns with Salvadorinho and Teixeira (2021), who note that lean, digitized manufacturing systems must coexist with stable human industrial relations to avoid operational paralysis.

5.2 Theme B: The MSME Digital Divide in Bhosari and Chinchwad

Interviews with HR managers from smaller industrial setups in Bhosari revealed a completely different technological reality. Here, AI tools are viewed with skepticism not because of algorithmic bias, but due to basic infrastructural deficits.

Interview Participant No. 11 (HR Head, Precision Component Component Manufacturer, Bhosari):

"Corporate case studies talk about AI sentiment analysis and automated talent mapping. In the smaller job shops, our primary challenge is getting contract labourers to properly register their biometric parameters on cloud applications. Heavy AI modules are financially out of reach; we need light systems that handle multi-shift payrolls without crashing."

5.3 Theme C: Algorithmic Opacity and "Black Box" Anxiety

Mid-level HR professionals frequently expressed discomfort over their inability to explain how prescriptive AI modules arrived at talent decisions. This directly validates the high quantitative Technological Anxiety (*TA*) score.

Interview Participant No. 7 (Assistant Manager - Talent Management, Chinchwad Engineering Firm):

"Our system now includes a predictive turnover tool that scores employees on their flight risk. When it gives a high risk percentage to a core design engineer, I cannot see the background parameters it weighed. If I stop promoting them based on a hidden machine calculation, I risk damaging trust without a solid explanation."

6. Strategic Recommendations: The Strategic-Augmented HR Framework

To restore system equilibrium as outlined by Socio-Technical Systems (STS) Theory, PCMC manufacturing organizations should adopt a targeted, three-layered strategy:

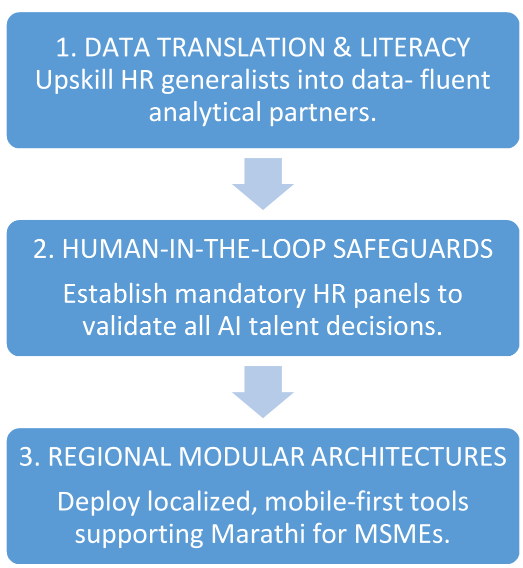


Fig 6.1: Model based on STS Theory

1. **Mandate Data Literacy and Analytical Training:** HR generalists must be actively upscaled to decode data visualizations into strategic talent retention initiatives, transforming them from data collectors to data translators.

2. **Establish Human-in-the-Loop Safeguards:** AI recommendations regarding hiring filters, safety adjustments, or disciplinary flags must never operate autonomously. A mandatory review panel of HR personnel must act as the final decision authority to counter data bias and maintain industrial trust.

3. **Deploy Tailored Modular Architectures for MSMEs:** Vendor partners should provide light, scalable, mobile-first AI modules (incorporating regional languages like Marathi) to ensure blue-collar workers can easily interface with digital portals for leave and attendance tracking.

7. Limitations and Scope for Future Research

- **Geographical Boundary:** The findings are heavily customized to the specific industrial ecosystem of PCMC MIDC and may not perfectly mirror service-oriented or IT clusters like Hinjawadi.

- **Survivorship Bias:** The data is naturally skewed toward enterprises that have successfully survived market changes and adopted digital transitions, potentially underrepresenting micro-scale units that operate manually.

- **Future Scope:** Future research could run longitudinal studies tracking how the formal implementation of the new Indian Labour Codes interacts with automated HR compliance engines over a multi-year period.

8. Conclusion

The integration of Artificial Intelligence within the HR departments of PCMC MIDC's manufacturing sector is no longer an optional luxury but a core requirement for remaining competitive. As shown through our Socio-Technical analysis, the technical capabilities of automated software have progressed faster than the social capabilities of human operators, creating a distinct skills deficit and structural anxiety.

AI has successfully stripped away layers of administrative friction, empowering HR personnel to step into higher-value roles focused on organizational design, upskilling strategies, and safety protocols on the shop floor. Ultimately, the successful future of industrial work relies on a balanced ecosystem where technology excels at optimization, and human HR professionals remain the vital custodians of empathy, ethical balance, and employee trust.

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