Ethical and Organizational Challenges of Artificial Intelligence Adoption in Human Resource Management

Sub-field: Strategic Human Resource Management · Technology Adoption · Organizational Behaviour

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ABSTRACT

The diffusion of Artificial Intelligence (AI) into the core functions of Human Resource Management (HRM) workforce planning, recruitment, scheduling, performance management and attrition prediction has advanced faster than the managerial capability and governance structures needed to deploy it responsibly. This paper examines the ethical and organizational challenges of AI-enabled HRM in India's textile and apparel sector, an industry that is India's second-largest employer after agriculture and is structurally reliant on low-skilled, contractual and predominantly female labour. Adopting a conceptual-analytical methodology and drawing on the Technology–Organization–Environment (TOE) framework and the Technology Acceptance Model (TAM), the study synthesizes technology-adoption, ethics-and-governance and India-specific literature into an integrated framework of adoption drivers, challenge clusters and value/risk outcomes. Three interlocking clusters of challenge are identified: ethical (algorithmic bias, erosion of consent-based privacy, opacity of automated decisions and threats to the dignity of labour); organizational (skill deficits, weak AI-governance structures, resistance to change and disproportionate compliance cost for micro, small and medium enterprises); and regulatory-compliance (statutory ambiguity around automated separation, cross-border data flows and the absence of a dedicated algorithmic-accountability regime). The paper argues that although the business case for AI-HRM adoption in India is increasingly well-evidenced, the governance and change-management case lags behind, and that the textile sector's labour-intensity and vulnerable workforce composition demand sector-specific managerial safeguards human-in-the-loop review of automated separation and disciplinary decisions, algorithmic impact assessments embedded in HR governance, and capacity-building for MSME clusters. Managerial and policy implications are offered for top management, the HR function, industry associations and policymakers, aimed at reconciling productivity gains from AI with the organizational values of fairness, transparency and the dignity of work.

Keywords: Artificial Intelligence; Strategic HRM; Technology Adoption; TOE Framework; Algorithmic Management; Change Management; HR Analytics; Textile Sector; India.

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1. INTRODUCTION

Artificial Intelligence has migrated from the periphery of enterprise information technology to the operational core of Human Resource Management. Applicant-tracking systems now screen resumes using natural-language-processing models; workforce-scheduling algorithms allocate shifts on factory floors; sentiment-analysis tools monitor employee communication for engagement and attrition risk; and predictive models increasingly inform decisions on promotion, transfer and separation. In India this transition has proceeded rapidly, with large organisations leading adoption while labour-intensive, MSME-dominated sectors such as textiles lag behind in both capability and governance readiness (“AI-Driven Human Resource Management in India,” 2025).

India's textile and apparel industry occupies a distinctive position in this transition. It is the country's second-largest source of direct and indirect employment, absorbing a workforce that is disproportionately female, contractual, semiliterate and concentrated in tier-II and tier-III industrial clusters such as Tiruppur, Surat, Ludhiana and Bhilwara (Ministry of Textiles, 2025). The industry's shift from Industry 4.0 automation toward AI-enabled, human-centric HR practice encompassing predictive analytics, smart recruitment, digital skilling platforms and AI-driven workforce planning has been documented as a defining feature of India's manufacturing transformation in 2026 ("Forging the Future," 2026). Yet the very characteristics that make the sector economically significant its reliance on low-bargaining-power labour, thin HR departments and fragmented MSME ownership also make it acutely vulnerable to the managerial hazards of algorithmic management: opaque hiring filters that may encode gender proxies, biometric and productivity-tracking systems that raise privacy concerns, and automated disciplinary or separation recommendations issued without meaningful human oversight.

This paper approaches these issues as a problem of management rather than of doctrine. Its central premise is that the ethical and organizational challenges of AI-enabled HRM cannot be assessed in the abstract; they must be located within the specific organizational, workforce and institutional conditions in which adoption occurs. The regulatory environment the constitutional right to privacy, the Digital Personal Data Protection Act, 2023, the four consolidated Labour Codes and the India AI Governance Guidelines, 2025 is treated here not as the object of study but as one component of the external environment shaping adoption decisions, consistent with the environmental dimension of the TOE framework.

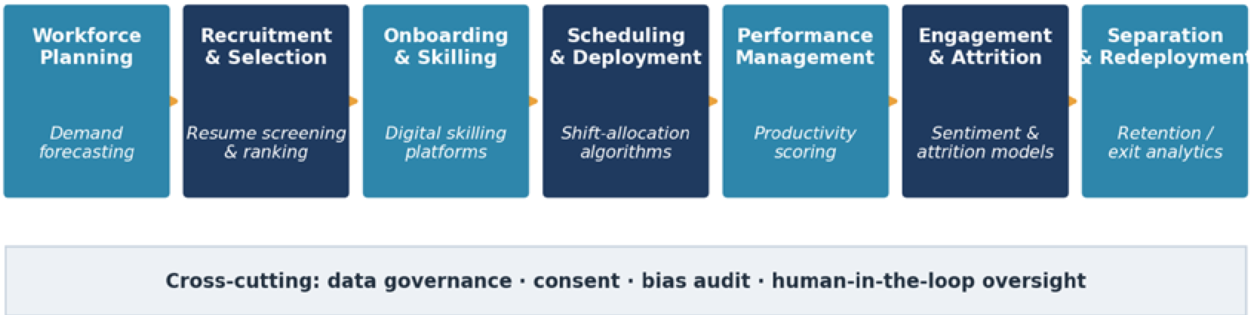

Figure 1. AI applications mapped across the HRM value chain in the textile sector, with cross-cutting governance requirements.

1.1 Statement of the Problem

Indian textile manufacturers and exporters are adopting AI-based HR tools at a pace that outstrips the maturity of their internal governance frameworks and change-management capability. HR functions designed around human decision-making are being asked to absorb algorithmic hiring, automated performance rating and machine-recommended separation without commensurate investment in data governance, employee communication or oversight. At the same time, the external environment data-protection rules, AI-governance guidance and labour regulation remains largely sector-agnostic and principle-based, offering limited operational guidance to a labour-intensive, MSME-dominated industry. The result is an accountability and capability gap precisely in the sector where the workforce is least equipped to assert its interests.

1.2 Objectives of the Study

- To map the ethical challenges bias, privacy, transparency and dignity arising from AI-enabled HRM practices in India's textile sector.
- To analyse the organizational barriers skill, cost, governance and culture that shape the manner of AI adoption in textile-sector HRM through a technology-adoption lens.
- To assess how the external (regulatory and institutional) environment conditions responsible adoption of algorithmic HR practices.
- To formulate sector-specific managerial and policy recommendations for top management, HR practitioners, industry associations and policymakers.

1.3 Research Questions

- What are the principal ethical risks generated by the deployment of AI in recruitment, appraisal and disciplinary functions within India's textile sector?
- Which technological, organizational and environmental factors most strongly enable or inhibit AI-HRM adoption in textile MSMEs?
- How do these challenges differ across worker categories and between large exporters and smaller units?
- What managerial and institutional interventions would best reconcile productivity gains from AI with organizational fairness and the protection of a vulnerable workforce?

1.4 Significance of the Study

The study contributes to the strategic-HRM and technology-adoption literature in three ways. First, it extends the TOE framework developed largely for IT and platform contexts to a labour-intensive manufacturing setting with distinctive workforce characteristics. Second, it integrates three previously separate literatures (technology adoption, algorithmic ethics and India-specific sectoral evidence) into a single managerial framework. Third, it translates abstract governance principles into concrete, MSME-scaled managerial practices, offering practitioners an actionable agenda rather than a purely normative critique.

1.5 Research Methodology

The study adopts a conceptual-analytical methodology. It synthesizes peer-reviewed journal articles, government and policy documents (NITI Aayog approach papers, the India AI Governance Guidelines, 2025, and Press Information Bureau releases) and industry reports on AI adoption in Indian manufacturing and textiles, and organises the resulting evidence within an established technology-adoption framework. Given the conceptual character of the paper, no primary field survey of textile establishments was conducted; the findings presented in Part 5 are accordingly findings of literature and framework synthesis. The figures presenting readiness profiles, driver/barrier salience and vulnerability are explicitly illustrative they operationalise qualitative patterns identified in the reviewed literature rather than report primary measurements. The paper recommends a follow-on empirical (survey- and interview-based) study of textile clusters as a natural extension of this work.

1.6 Scope and Limitations

The study is confined to India's organised and semi-organised textile and apparel manufacturing sector and does not extend to the handloom or artisanal cottage sector, whose labour relations differ substantially. Several external-environment instruments discussed notably the Rules under the Digital Personal Data Protection Act, 2023 and the Central Rules under the four Labour Codes remained in draft or partially notified form as of July 2026; the analysis is current to that date and should be read subject to subsequent developments. The conceptual figures are indicative and are intended to structure discussion, not to substitute for primary measurement.

Table 1. AI applications, management functions and illustrative textile-sector use cases

HRM function	AI application	Illustrative textile-sector use	Primary risk
Workforce planning	Demand forecasting & headcount analytics	Predicting seasonal labour demand across export order cycles	Over/under-staffing; opacity
Recruitment & selection	Resume screening & candidate ranking	Automated shortlisting for supervisory and machine-operator roles	Algorithmic bias
Onboarding & skilling	Adaptive digital-skilling platforms	Multilingual, role-based training on smart shop floors	Digital-literacy exclusion
Scheduling & deployment	Shift-allocation optimisation	Algorithmic rostering across shifts and production lines	Fairness; work intensification
Performance management	Productivity scoring & analytics	Continuous output monitoring of line workers	Surveillance; dignity
Engagement & attrition	Sentiment & attrition-risk models	Flagging attrition risk among contract workers	Privacy; profiling
Separation & redeployment	Retention / exit analytics	AI-informed retrenchment and redeployment recommendations	Automated separation

Source: author's synthesis of reviewed literature ("AI-Driven Human Resource Management in India," 2025; "AI-Driven Human Resource Management and Its Impact," 2026; "Forging the Future," 2026; Ministry of Electronics and Information Technology, 2025).

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

Scholarship on AI adoption in HRM has evolved along three broadly identifiable strands: (a) technology-adoption studies rooted in frameworks such as the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM); (b) ethics- and governance-oriented literature examining bias, transparency and accountability in algorithmic employment decisions; and (c) sector- and country-specific empirical studies, of which India-focused and textile-focused work remains comparatively sparse. Their relative weight in the reviewed corpus is depicted in Figure 6.

2.1 Technology-Adoption Theories

A substantial body of work applies the TOE framework to explain the determinants of AI-HRM adoption, modelling adoption as a function of technological factors (AI availability and compatibility), organizational factors (HR capability and readiness) and environmental factors (regulatory environment and leadership support) (Xia, 2026). This paper adapts that framework, in Part 3, to the specific organizational conditions of the Indian textile MSME. Complementary work in the Indian pharmaceutical sector identified organizational readiness, top-management support and perceived usefulness as significant antecedents of AI-HRM adoption (Goswami et al., 2023), while a 2026 meta-synthesis and systematic review catalogued multidimensional considerations including organizational readiness in the textile and garment industry of neighbouring Bangladesh as significant determinants of successful AI and big-data adoption ("Factors Influencing Artificial Intelligence Adoption," 2026), a finding of direct comparative relevance to the structurally similar Indian textile-export cluster. The Technology Acceptance Model complements TOE at the individual level, explaining how perceived usefulness and perceived ease of use shape supervisors' and workers' acceptance of AI tools on the shop floor.

2.2 Ethics and Governance Literature

A second strand interrogates the normative dimensions of algorithmic employment decisions. Indian scholarship has begun to examine the intersection of automated profiling, privacy and data protection, arguing that while recent regulation marks an important step, it falls short of a comprehensive framework for algorithmic accountability and that India would benefit from a more developed AI-governance architecture to protect individuals in an increasingly automated employment ecosystem ("Automated Profiling," 2026). A related line of enquiry addresses the gig economy and algorithmic governance, concluding that social-security provision for platform-mediated, AI-governed work remains limited in enforceability and inclusivity ("Gig Workers and Algorithmic Governance," 2025). These findings, developed principally in the platform context, are extended in Part 4 to the factory-floor context of textile manufacturing, where algorithmic scheduling and productivity-monitoring raise analogous though not identical concerns.

2.3 Sector-Specific and India-Focused Evidence

Literature specific to the Indian textile sector remains an emerging field. A qualitative study of generative-AI adoption among mid-career supervisors in textile manufacturing found socio-demographic factors, including age and prior digital exposure, to significantly shape acceptance and integration of AI tools on the shop floor ("Adoption of Generative Artificial Intelligence Tools," 2025). Industry-facing commentary has identified worker resistance, fear of job displacement, absence of governmental sectoral support, and data-security and quality-assurance concerns as the principal barriers to AI integration in Indian textile manufacturing ("Weaving the Future," 2025). At a broader HRM level, a 2026 study drawing on primary data from 312 HR and finance practitioners across Indian manufacturing, IT, service and retail firms found statistically significant positive associations between AI-HRM adoption and cost efficiency ("AI-Driven Human Resource Management and Its Impact," 2026), underscoring that the business case for AI-HRM adoption in India is increasingly well-evidenced even as the corresponding governance case lags behind.

2.4 Research Gap

The literature establishes with reasonable clarity that (a) AI-HRM adoption in India is accelerating and sector-differentiated; (b) it is occurring against a data-protection and AI-governance framework that is still maturing; and (c) the ethics literature has concentrated on the gig/platform economy and on manufacturing generally, rather than on the textile sector's distinctive combination of labour-intensity, feminised workforce and MSME fragmentation. This paper addresses that gap by integrating the technology-adoption, ethics-and-governance and India-specific-textile strands into a single managerial framework, examined against the workforce and institutional conditions of the sector in 2026.

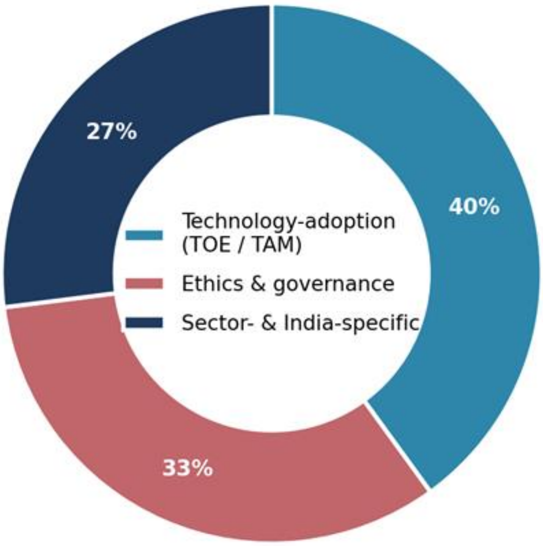

Figure 2. Thematic distribution of the reviewed literature across the three research strands (author's classification).

Table 2. Summary of key studies reviewed

Study (ref.)	Framework / lens	Focus	Key contribution
Xia (2026)	TOE / bibliometric	AI-HRM adoption determinants	Confirms tech, org and environment factors jointly drive adoption
Goswami et al. (2023)	Adoption antecedents	Indian pharma sector	Readiness, top-mgmt support, usefulness as antecedents
Factors Influencing AI Adoption (2026)	Systematic review	Multi-country incl. Bangladesh textiles	Organizational readiness central to adoption success
AI-Driven HRM in India (2025)	Descriptive	AI-HRM in India	Large firms lead; textiles lag in readiness
Automated Profiling (2026)	Governance analysis	Automated profiling & data protection	Accountability gap in algorithmic HR decisions
Adoption of Generative AI Tools (2025)	Qualitative / TAM	Textile supervisors	Socio-demographic factors shape AI acceptance
AI-Driven HRM & Cost Efficiency (2026)	Quantitative (n=312)	AI-HRM & cost efficiency	Positive link between AI-HRM and cost efficiency
Forging the Future (2026)	Industry perspective	Human-centric HR on the factory floor	Documents Industry 4.0→5.0 HR transition

Source: author's synthesis of the reviewed literature.

3. CONCEPTUAL FRAMEWORK

Building on the literature reviewed above, this paper proposes an integrated conceptual framework (Figure 1) that positions AI-HRM adoption as the outcome of three sets of antecedents technological, organizational and environmental consistent with the TOE tradition. Adoption, in turn, produces two categories of outcome: value outcomes (efficiency, quality and scalability) and risk outcomes (bias, privacy erosion, threats to dignity and industrial disputes). Crucially, the relationship between adoption and outcomes is moderated by the firm's governance capability human-in-the-loop review, documented AI-use policy and audit which determines whether adoption translates predominantly into value or into risk. A feedback loop captures how realised outcomes reshape organizational readiness and future adoption decisions.

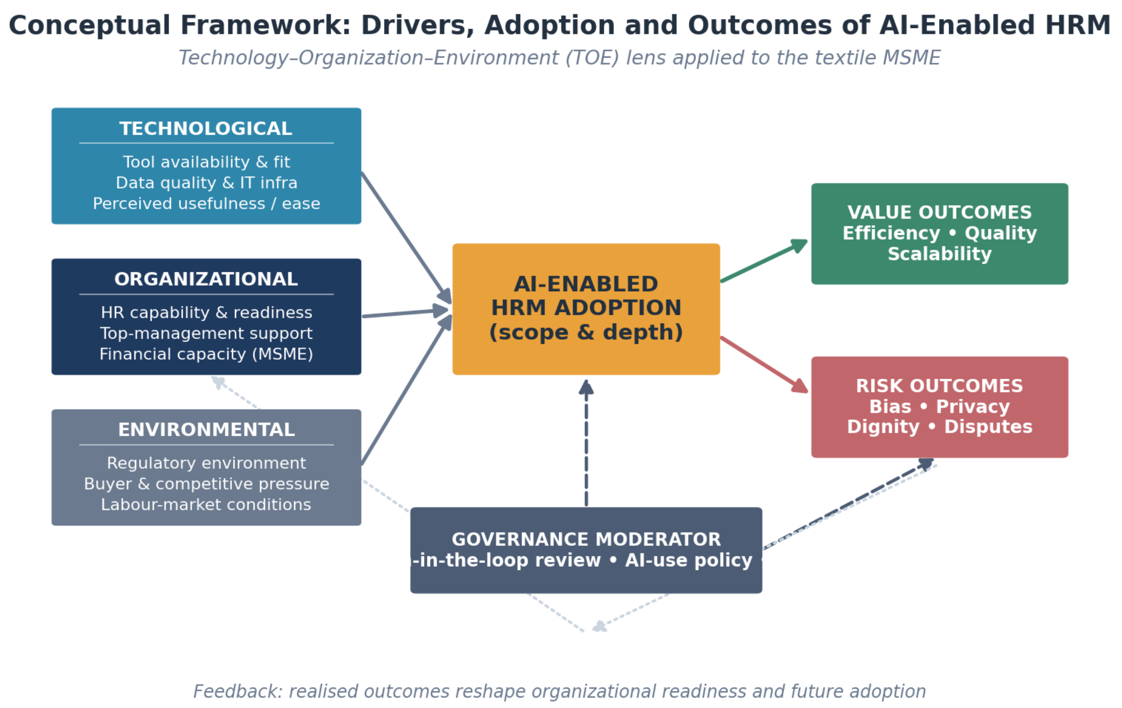

Figure 3. Conceptual framework: technological, organizational and environmental antecedents of AI-HRM adoption, moderated by governance capability, producing value and risk outcomes.

The managerial significance of the framework lies in the moderator. Two firms with identical adoption scope may experience sharply different outcomes depending on their governance maturity: absent human-in-the-loop review and bias audit, the same tool that delivers scheduling efficiency for one firm produces contested separations and reputational risk for another. The framework therefore reframes responsible AI not as a constraint on adoption but as the mechanism that converts adoption into sustainable value.

Table 3. TOE determinants of AI-HRM adoption in textile MSMEs

Dimension	Determinant	Condition in the textile MSME
Technological	Tool availability & compatibility	Off-the-shelf tools available but poorly localised for shop-floor use
Technological	Data quality & IT infrastructure	Fragmented, often paper-based HR records limit model reliability
Organizational	HR analytics capability	Thin, generalist HR functions with limited data-science skills
Organizational	Top-management support	Variable; strongest among large export-oriented units
Organizational	Financial capacity	Constrained; fixed compliance costs are proportionally heavier
Environmental	Regulatory environment	Principle-based, sector-agnostic; operational rules still maturing
Environmental	Buyer & competitive pressure	Global buyers' audit requirements can accelerate adoption

Source: author's adaptation of the TOE framework (Xia, 2026; Goswami et al., 2023) to textile-sector conditions.

4. ANALYSIS AND DISCUSSION

This Part classifies the challenges of AI-enabled HRM in the textile sector into three interlocking clusters ethical, organizational and regulatory-compliance depicted in Figure 3, and examines the managerial implications of each.

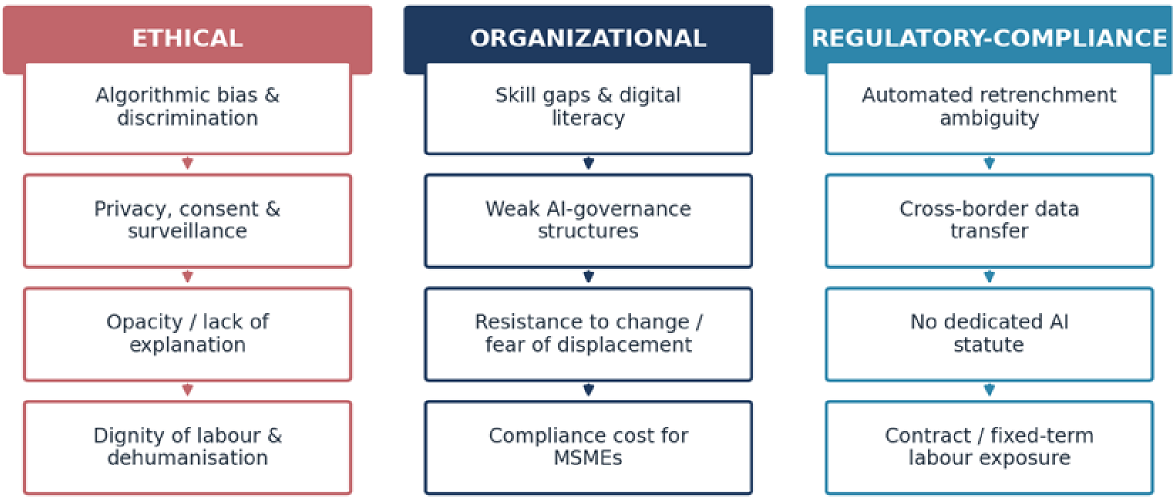

Figure 4. Taxonomy of ethical, organizational and regulatory-compliance challenges in AI-enabled HRM in the textile sector.

4.1 Ethical Challenges

4.1.1 Algorithmic Bias and Discrimination

Automated resume-screening and candidate-ranking tools trained on historical hiring data risk encoding and perpetuating past patterns of exclusion including gender-based exclusion, which is of acute relevance to a sector in which women constitute a substantial share of the shop-floor workforce yet remain under-represented in supervisory and managerial cadres. Where bias operates covertly through proxy variables (residential location, employment gaps, or names indicative of social group), it can evade informal fairness checks and reproduce structural disadvantage at scale and speed. From a management standpoint, the risk is not merely reputational: biased shortlisting narrows the talent pool, entrenches homogeneity in supervisory ranks, and exposes the firm to grievance and audit findings. The India AI Governance Guidelines, 2025 recognise algorithmic discrimination as a principal AI-related risk but, consistent with their light-touch philosophy, stop short of prescribing binding bias-audit obligations for private employers.

4.1.2 Privacy, Consent and Surveillance

Biometric attendance systems, productivity-tracking software and AI-enabled CCTV analytics, now common on Indian factory floors, constitute processing of personal data that triggers consent, purpose-limitation and data-minimisation obligations for employers acting as data fiduciaries. The managerial difficulty in the textile sector is that workers frequently lack the digital literacy to exercise consent-withdrawal and grievance rights meaningfully, rendering consent closer to a formality than a genuine choice. Continuous monitoring also carries a behavioural cost: surveillance intensity that exceeds a legitimate operational purpose can erode trust, depress discretionary effort and increase turnover outcomes squarely within the HR function's remit even where each discrete data-processing act is technically compliant.

4.1.3 Opacity and the Absence of Explanation

Where a worker is denied promotion, transferred, or placed on a performance-improvement plan on the recommendation of an opaque scoring algorithm, she typically has no access to the reasoning behind that recommendation. For managers, opacity undermines the procedural fairness on which perceived organizational justice depends; employees who cannot understand a decision are less likely to accept it and more likely to escalate it. Explainability is therefore not only an ethical desideratum but a change-management necessity: adoption without intelligible decision rationales invites resistance and dispute.

4.1.4 Dignity of Labour and Dehumanisation

Beyond discrete entitlements, algorithmic productivity-scoring and continuous biometric surveillance raise a broader dignitary concern. The reduction of a worker's performance to a continuously monitored numerical score, particularly in a sector already associated with intense production-line pressure, risks instrumentalising labour in a manner corrosive of engagement and organizational commitment. Sustainable performance management balances measurement with meaning; AI systems that optimise output while ignoring the human experience of work tend to generate the very attrition they were meant to predict.

4.2 Organizational Challenges

Applying the TOE framework, the textile sector scores poorly on the organizational dimension of AI readiness. Figure 4 contrasts the readiness profiles of large integrated exporters and MSME units across six TOE-derived dimensions; Table 5 summarises the same asymmetry in narrative form.

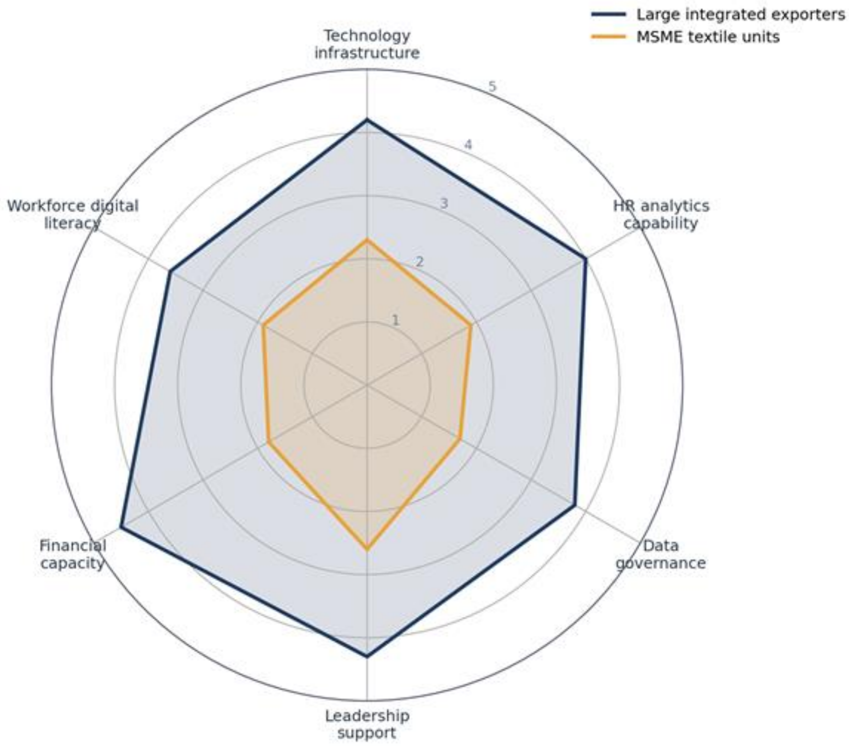

Figure 4. Illustrative AI-HRM readiness profiles of large exporters versus MSME units across six TOE dimensions (1 = nascent, 5 = mature).

4.2.1 Skill Gaps and Digital Literacy

HR functions in MSME textile units are frequently thin, generalist and lacking in data-science or AI-governance capability. Where supervisors themselves display generational and socio-demographic variance in AI-tool acceptance ("Adoption of Generative Artificial Intelligence Tools," 2025), the risk of inconsistent, poorly audited AI deployment across shifts and units rises correspondingly. Building analytics literacy within HR and basic AI awareness among supervisors and workers is a precondition for responsible adoption, not an optional supplement to it.

4.2.2 Weak AI-Governance Structures

Few textile-sector employers maintain a documented AI-use policy, an internal oversight committee, or a defined escalation pathway for algorithmic error governance infrastructure that larger IT- and BFSI-sector employers have begun to institutionalise. The absence of such structures increases both ethical risk (undetected bias) and organizational risk (inability to demonstrate accountability to buyers, auditors and regulators).

4.2.3 Resistance to Change and Fear of Displacement

Industry commentary consistently identifies worker and, at times, middle-management resistance driven by apprehension of job displacement as a significant barrier to AI adoption in Indian textile manufacturing ("Weaving the Future," 2025). This is a classic change-management problem: unaddressed, resistance manifests as low utilisation, workarounds and, at the extreme, industrial dispute. Effective adoption therefore depends less on the technology than on communication, participation and credible reskilling commitments.

4.2.4 Cost of Compliance for MSMEs

The sector's MSME-dominated ownership means the fixed costs of data-governance infrastructure, algorithmic audit and staff training are proportionally more burdensome than for large, capital-intensive employers a structural asymmetry that risks entrenching a two-tier landscape in which only larger exporters can credibly claim responsible AI governance. Shared, cluster-level compliance facilities are one managerial response explored in Part 6.

4.3 Regulatory-Compliance Challenges (the Environmental Dimension)

Consistent with the framework, the external regulatory environment is analysed here as a factor conditioning managerial choice rather than as the object of study. Four features are salient.

- **Automated separation.** The Industrial Relations Code, 2020 is silent on whether a separation decision substantially generated by an AI performance-management system satisfies the requirement of a stated, bona fide reason creating uncertainty that prudent managers should resolve through human-in-the-loop review.

- **Cross-border data transfer.** Global exporters routinely transmit employee and production data to overseas buyers for compliance audits; the residual discretion of government to restrict such transfers creates planning uncertainty for export-oriented HR data flows.
- **Absence of a dedicated AI statute.** India relies on principle-based guidance rather than enforceable algorithmic-accountability duties, leaving much to firm-level governance discretion.
- **Contract and fixed-term labour.** A large share of textile production is undertaken through contract and fixed-term labour, whose weaker bargaining position compounds the risk that AI tools applied to this segment operate with the least oversight where the human cost of error is highest.

Figure 5 summarises the relative salience of the principal drivers and barriers to adoption identified across the reviewed literature, and Figure 8 shows how exposure to algorithmic HR decisions is concentrated among the sector's most vulnerable worker categories.

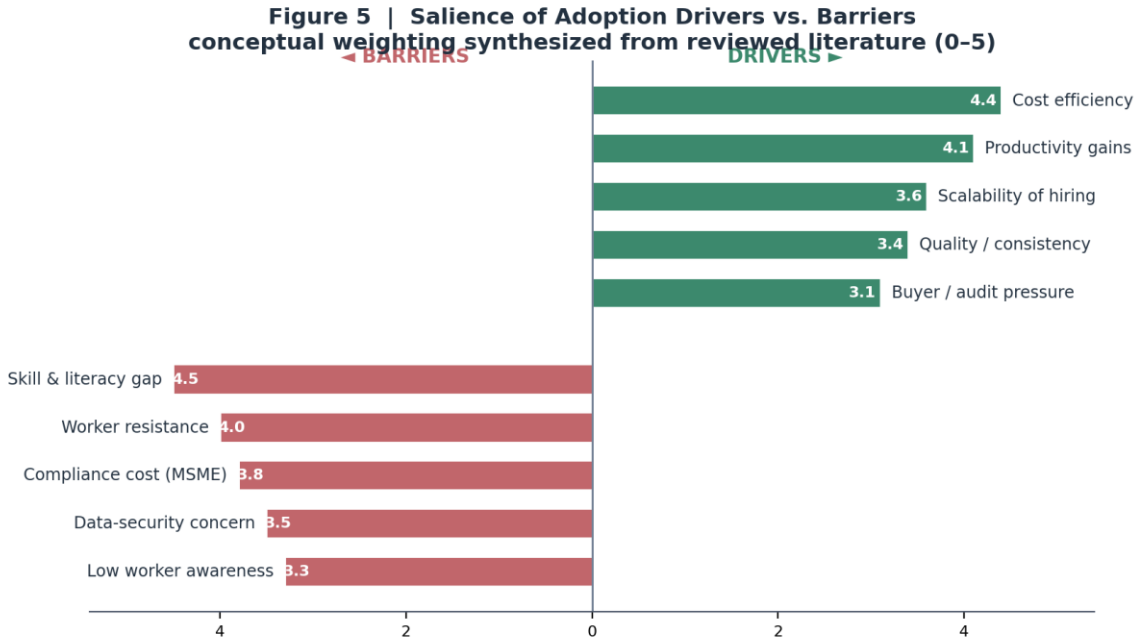

Figure 5. Conceptual salience of AI-HRM adoption drivers and barriers, synthesized from the reviewed literature.

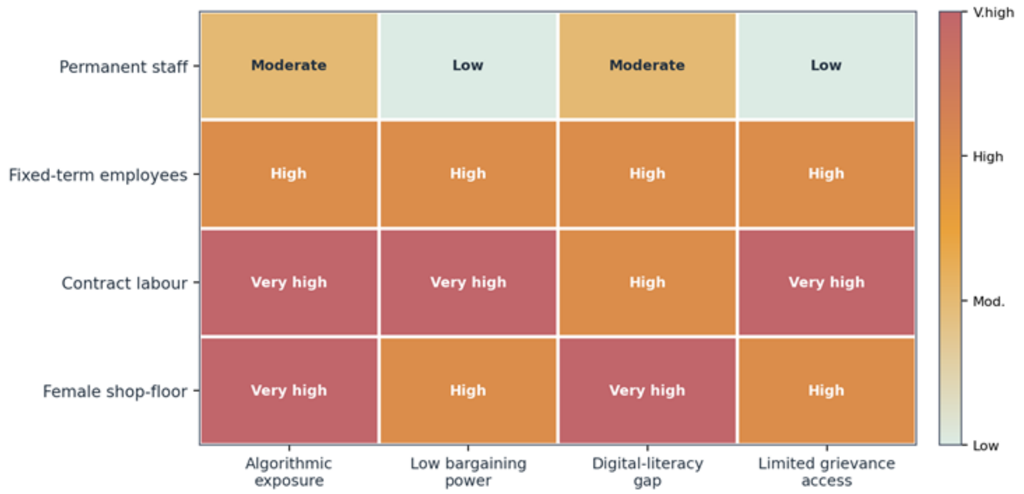

Figure 6. Workforce vulnerability to algorithmic HR decisions across worker categories and exposure dimensions (illustrative).

Table 4. Challenge clusters mapped to managerial implications and responses

Cluster	Core challenge	Managerial response
Ethical	Algorithmic bias	Pre-deployment and periodic bias testing; diverse training data; audit trail

Cluster	Core challenge	Managerial response
Ethical	Privacy & surveillance	Purpose limitation; data minimisation; proportionate monitoring; clear notice
Ethical	Opacity	Plain-language decision rationales; explainable models for HR use
Ethical	Dignity	Balance measurement with autonomy; avoid pure output-scoring
Organizational	Skill gaps	HR analytics upskilling; supervisor and worker AI-awareness training
Organizational	Weak governance	AI-use policy; oversight committee; error-escalation pathway
Organizational	Resistance	Participative change management; reskilling and redeployment commitments
Organizational	MSME cost	Cluster-level shared compliance facilities; scaled model policies
Regulatory	Automated separation	Mandatory human-in-the-loop review of separation and discipline
Regulatory	Data transfer	Data-transfer mapping; contractual safeguards with buyers

Source: author's analysis.

Table 5. AI-HRM readiness: large integrated exporters versus MSME units

Dimension	Large integrated exporters	MSME textile units
Technology infrastructure	Enterprise HRIS; digitised records	Fragmented, often paper-based records
HR analytics capability	Dedicated analytics roles emerging	Generalist HR; minimal analytics skill
Data governance	Formal policies developing	Largely absent
Leadership support	Strong, buyer-driven	Variable; owner-dependent
Financial capacity	Able to absorb compliance cost	Compliance cost proportionally heavy
Workforce digital literacy	Moderate, improving	Low; language and access barriers
Governance maturity (Fig. 7)	Integrated (Stage 4)	Experimenting (Stage 2)

Note: qualitative synthesis; positions correspond to the maturity model in Figure 7.

Table 6. Adoption barriers and change-management responses

Barrier	Manifestation	Change-management response
Skill & literacy gap	Low utilisation; input errors	Role-based training; multilingual interfaces
Worker resistance	Workarounds; grievance; disputes	Early communication; participation; reskilling
Compliance cost	Deferred or partial adoption	Shared cluster facilities; phased rollout
Data-security concern	Reluctance to digitise records	Security safeguards; transparent data handling
Low worker awareness	Uninformed consent; mistrust	Awareness campaigns; accessible notice

Source: author's synthesis of ("Adoption of Generative Artificial Intelligence Tools," 2025; "Weaving the Future," 2025).

5. FINDINGS

On the basis of the analysis in Part 4, the following findings are drawn. These are findings of literature and framework synthesis rather than of primary field research, and are framed accordingly.

- **Governance case lags the business case.** Empirical evidence links AI-HRM adoption to cost efficiency in Indian organisations ("AI-Driven Human Resource Management and Its Impact," 2026), creating a commercial incentive for adoption that is not matched by an equally developed governance or change-management incentive.
- **The organizational dimension is the binding constraint.** Across the TOE dimensions, textile MSMEs are weakest on HR analytics capability, data governance and financial capacity making organizational readiness, not technology availability, the decisive factor.
- **Risk concentrates in vulnerable worker categories.** Contract, fixed-term and predominantly female shop-floor workers face the highest exposure to unaudited algorithmic decision-making and the lowest practical capacity to contest it (Figure 8).
- **Governance capability is the pivotal moderator.** Whether adoption yields value or risk depends less on the tool than on human-in-the-loop review, documented policy and audit capabilities most textile MSMEs currently lack.
- **Sector-blindness of external guidance.** Neither data-protection nor AI-governance instruments contain textile- or manufacturing-specific guidance, assuming a compliance sophistication atypical of MSME employers.
- **A two-stage maturity gap.** Large exporters sit around the integrated stage of AI-HRM maturity while most MSME units remain at the experimenting stage (Figure 7), implying that interventions must be scaled differently for the two segments.

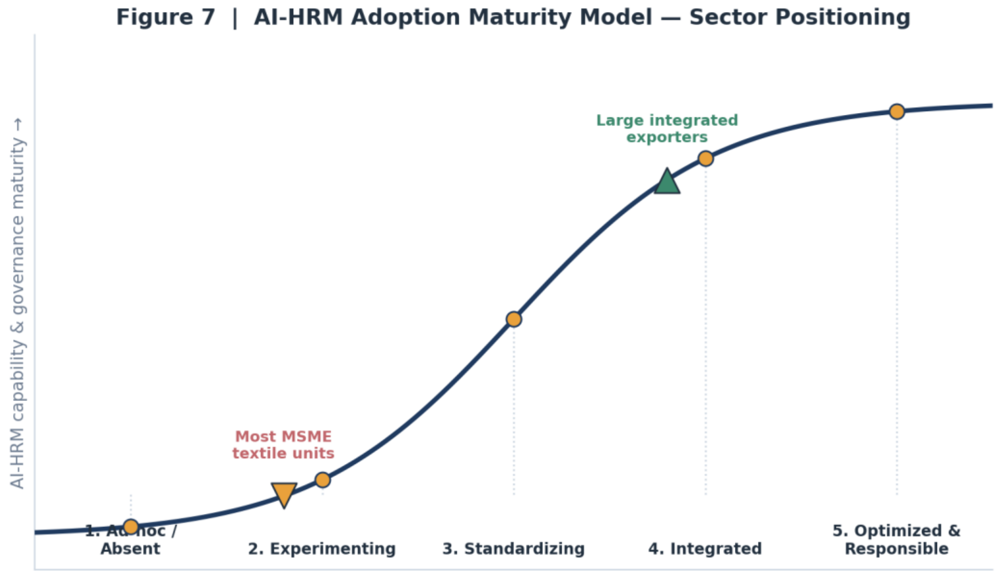

Figure 7. AI-HRM adoption maturity model, showing the positioning of MSME units and large exporters.

6. MANAGERIAL AND POLICY IMPLICATIONS

6.1 For Top Management and Strategy

- Treat responsible AI governance as a value driver, not a cost centre: make human-in-the-loop review and bias audit standard operating procedure for any HR system affecting continuation, pay or working conditions.
- Sequence adoption to organizational readiness: invest in data quality, HR capability and change management before scaling algorithmic decision-making.
- Designate accountability for AI-related HR systems at senior level, with a defined escalation pathway for algorithmic error.

6.2 For the HR Function

- Build HR analytics literacy and appoint a data-protection point of contact with explicit responsibility for AI-enabled HR systems.
- Maintain plain-language decision rationales for AI-influenced decisions, accessible to the affected worker, to preserve procedural fairness.
- Design proportionate monitoring: collect the minimum data necessary for a legitimate HR purpose and communicate its use clearly.
- Embed reskilling and redeployment commitments into adoption plans to convert resistance into engagement.

6.3 For Industry Bodies

- Develop a voluntary Code of Practice on Responsible AI in Textile HRM, including model AI-use policies scaled for MSME adoption.
- Establish shared, cluster-level compliance-support facilities to offset the fixed cost of responsible governance for smaller units (e.g., in Tiruppur, Surat and Ludhiana).
- Run sector-wide digital-literacy and AI-awareness programmes targeted at shop-floor supervisors and workers, informed by the socio-demographic variance in acceptance documented in recent research ("Adoption of Generative Artificial Intelligence Tools," 2025).

6.4 For Policymakers

- Issue sector-specific guidance clarifying how consent, purpose-limitation and data-fiduciary obligations apply to biometric attendance and productivity-tracking systems on factory floors.
- Provide for meaningful human review prior to any separation, transfer or disciplinary action substantially based on an automated recommendation, and extend grievance mechanisms to expressly cover algorithmic HR decisions in a low-literacy-accessible format.
- Develop sector-specific translations of the India AI Governance Guidelines, 2025 for labour-intensive manufacturing, without displacing their broader light-touch philosophy.

6.5 Directions for Future Research

The conceptual findings of this paper would benefit from validation through a structured empirical study a stratified survey and semi-structured interviews across textile clusters such as Tiruppur, Surat and Ludhiana examining actual (as opposed to policy-projected) patterns of AI-HRM deployment, worker awareness of data-protection rights, and the incidence of AI-linked grievances. Such a study would allow the readiness profiles and vulnerability patterns illustrated in Figures 4 and 8 to be empirically weighted and would strengthen the evidentiary basis for the interventions recommended above.

Table 7. Summary of recommendations by stakeholder

Stakeholder	Priority action	Intended outcome
Top management	Standardise human-in-the-loop review & bias audit	Convert adoption into sustainable value
HR function	Build analytics literacy; maintain decision rationales	Procedural fairness; trust
Industry bodies	Code of practice; shared compliance facilities	Responsible adoption at MSME scale
Policymakers	Sector-specific guidance; grievance access	Protection for vulnerable workers
Researchers	Empirical validation across clusters	Evidence-based interventions

Source: author's analysis.

CONCLUSION

The adoption of Artificial Intelligence in Human Resource Management is neither ethically nor organizationally neutral; it redistributes information, power and risk within the employment relationship in ways that thin, generalist HR functions are often unprepared to manage. India's textile sector, precisely because of its scale, labour-intensity and structural vulnerability, offers a critical test case for whether AI-HRM adoption can be governed responsibly. This paper has argued that the business case for adoption has outpaced the governance and change-management case, that the binding constraint lies in organizational readiness rather than in technology availability, and that governance capability human-in-the-loop review, documented policy and audit is the pivotal moderator determining whether adoption yields value or risk. Bridging the gap will require coordinated action across strategy, the HR function, industry self-regulation and public policy an integration the recommendations in Part 6 are designed to advance, and toward which the empirical research agenda outlined in Part 6.5 is offered as a necessary next step.

REFERENCES

1. *Adoption of generative artificial intelligence tools among supervisors in the second half of their working life: A qualitative study. (2025). Premier Science.*
2. *AI-driven human resource management and its impact on cost efficiency and financial sustainability: Evidence from Indian organizations. (2026). Journal of Marketing & Social Research, 3(1), 120–129.*
3. *AI-driven human resource management in India. (2025). Kuey Journal.*

4. *Automated profiling, privacy rights, and gaps in India's data protection framework. (2026). IRE Journals.*
5. *Factors influencing artificial intelligence adoption in human resource management: A meta-synthesis and systematic review of multidimensional considerations. (2026). Journal of Work-Applied Management, 18(1), 47. Emerald Publishing.*
6. *Forging the future: How AI and human-centric HR are revolutionizing the manufacturing floor in 2026 An Indian perspective. (2026). International Education and Research Journal, 12.*
7. *Gig workers and algorithmic governance under Indian labour law: A doctrinal analysis. (2025).*
8. *Goswami, M., Jain, S., Alam, T., Deifalla, A. F., Ragab, A. E., & Khargotra, R. (2023). Exploring the antecedents of AI adoption for effective HRM practices in the Indian pharmaceutical sector. Frontiers in Pharmacology, 14, Article 1215706.*
9. *Ministry of Electronics and Information Technology. (2025). India AI governance guidelines. Government of India.*
10. *Ministry of Labour & Employment. (2025, November 21). Government announces implementation of four Labour Codes to simplify and streamline labour laws [Press release]. Press Information Bureau, Government of India.*
11. *Ministry of Textiles. (2025). Annual report 2024–25. Government of India.*
12. *NITI Aayog. (2021). Responsible AI for all: Approach document for India (Parts I & II).*
13. *Weaving the future: How AI is reshaping India's textile industry. (2025). Fashion Value Chain.*
14. *Xia, Z. (2026). Mapping and testing AI adoption in human resource management: A bibliometric review and TOE-based quantitative analysis. Quality & Quantity.*
15. *Legal and Policy Instruments Referenced*
16. *The Constitution of India, 1950, Articles 14, 15 and 21.*
17. *The Digital Personal Data Protection Act, 2023 (Act No. 22 of 2023).*
18. *The Information Technology Act, 2000 (Act No. 21 of 2000).*
19. *The Code on Wages, 2019; the Industrial Relations Code, 2020; the Code on Social Security, 2020; and the Occupational Safety, Health and Working Conditions Code, 2020.*
20. *Justice K. S. Puttaswamy (Retd.) v. Union of India, (2017) 10 SCC 1.*