

# Green Human Resource Management Practices and Their Impact on Organisational Sustainability Performance: Evidence from Indian Manufacturing

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## Abstract

Green human resource management (Green HRM) translates environmental strategy into the daily decisions of recruiting, training, appraising and paying employees. Indian manufacturing has adopted these practices unevenly, and the mechanism connecting them to sustainability outcomes has not been tested with sector-level data from India. We surveyed 480 managers across 96 firms in the automotive, pharmaceutical and textile sub-sectors and combined the survey with 24 semi-structured interviews. Structural equation modelling showed that green training had the strongest effect on environmental performance ( $\beta = 0.47$ ,  $p < 0.001$ ), with green recruitment second ( $\beta = 0.33$ ,  $p < 0.001$ ); employee green behaviour mediated 54 per cent of the total effect on organisational sustainability performance, and firms holding ISO 14001 certification showed 28 per cent higher Green HRM adoption than uncertified firms. The pharmaceutical sub-sector led on training-related adoption while textile firms lagged on every practice we measured. These results indicate that Green HRM affects sustainability mainly by changing what employees do day to day, not only by changing formal policy, and that certification status conditions how far that change can go.

**Index Terms**—Green HRM, environmental performance, employee green behaviour, organisational sustainability, ISO 14001, Indian manufacturing, mixed methods.

## I. Introduction

A factory in Faridabad can hold an ISO 14001 certificate, publish an annual sustainability report and still discharge untreated effluent on a night shift when no auditor is present. The gap between documented environmental policy and shop-floor behaviour is where Green human resource management operates. It is the set of HR practices, recruitment, training, performance appraisal and compensation, redesigned to select, shape and reward the behaviours that environmental strategy requires [92], [120].

Indian manufacturing sits under three overlapping pressures that make this gap consequential. Export buyers increasingly require supplier-level environmental disclosure; the Ministry of Environment, Forest and Climate Change has tightened enforcement of the Water (Prevention and Control of Pollution) Cess and hazardous-waste rules since 2021; and domestic energy costs have risen enough that waste reduction now shows up on the same balance sheet as compliance. Firms have responded with environmental management systems, but a system only changes outcomes if the people running it change what they do.

Three sub-sectors illustrate the range of the problem. Automotive component manufacturers operate under supplier scorecards from original equipment manufacturers that increasingly weight carbon and water metrics. Pharmaceutical manufacturers face effluent standards specific to active pharmaceutical ingredient production, some of the strictest in Indian industry. Textile manufacturers, concentrated in Tiruppur, Surat and Ludhiana, face the heaviest reputational exposure over dyeing effluent yet report the lowest average capital available for environmental retrofits. A single national estimate of "Green HRM adoption" would erase exactly the variation that matters for policy and for firm strategy.

We ask three questions. First, which Green HRM practices, recruitment, training, performance management or compensation, carry the largest effect on environmental performance in Indian manufacturing, and by how much. Second, does that effect operate directly on firm-level outcomes or through a change in what individual employees do, that is, through employee green behaviour as a mediator. Third, does formal certification, specifically ISO 14001, change the size of Green HRM adoption or only its visibility.

We answer these questions with a sequential explanatory mixed-methods design: a structured survey of 480 managers across 96 firms, analysed with structural equation modelling, followed by 24 semi-structured interviews used to explain the quantitative pattern rather than to test it independently. The contribution is threefold. We provide the first sector-disaggregated estimate of Green HRM effects for Indian manufacturing; we quantify the share of the total effect that runs through employee green behaviour rather than through formal systems alone; and we identify where technology, predictive analytics, IoT-based monitoring and related tools now used elsewhere in Indian industrial research, could plausibly extend Green HRM measurement and practice, a direction we return to in Section VII.

Section II reviews the Green HRM literature and the broader body of applied machine-learning and sensing research from which several of the extensions in Section VII are drawn. Section III sets out the theoretical framework and hypotheses. Section IV describes the sample, instruments and mixed-methods procedure. Sections V and VI report and interpret the results. Section VII discusses implications for managers and policy, and Section VIII concludes.

## **II. Literature Review**

### **A. Green Recruitment and Selection**

Green recruitment screens candidates for pre-existing environmental values and signals organisational identity to the external labour market. Firms that mention environmental credentials in job postings attract applicants who already hold pro-environmental attitudes, which lowers the training burden later. This logic parallels feature-selection work in unrelated machine-learning domains, where selecting the right inputs before training a model determines how much correction the model needs afterward [5], [16], [17].

Recruitment-stage signalling is inexpensive relative to training and compensation redesign, which is one reason firms adopt it first. It is also the practice most easily observed by outsiders, since job postings are public, so recruitment-level Green HRM can overstate a firm's actual environmental commitment if it is not followed by training and appraisal changes; we test this concern directly in Section V.

### **B. Green Training and Development**

Training converts stated environmental values into specific competences, waste segregation, energy-efficient equipment operation, spill response, and is repeatedly identified in adjacent literatures as the practice with the largest measurable effect on operational outcomes. Analogous findings recur in technical domains outside HRM: hyperparameter-tuned models trained on adequately prepared data consistently outperform architecturally superior models trained on poorly prepared data [4], a pattern that supports our expectation that training quality, not the mere existence of a training programme, drives the environmental-performance effect.

Training effects are also sector-contingent. Pharmaceutical manufacturing requires standard operating procedures for API waste handling that are already detailed and auditable, which gives green training a ready-made delivery channel; automotive component plants have shorter production-line dwell times per worker, which compresses training windows; textile units rely more heavily on contract labour with high turnover, which erodes the return on any training investment before it compounds. We test this contingency formally in Section V rather than asserting it.

### **C. Green Performance Management and Compensation**

Performance management embeds environmental indicators into appraisal criteria, and compensation ties pay or promotion to those indicators. Both practices depend on measurement: an appraisal criterion that cannot be measured reliably becomes symbolic rather than operative, which is why several firms in our interview sample had adopted green performance criteria on paper years before any green compensation followed.

The measurement problem here is not unlike the one addressed by predictive analytics applied to energy optimisation and resource allocation in other industrial contexts [129], [130], [3], [8], where a model is only as useful as the sensor data feeding it. A plant that lacks metering for departmental energy or water use cannot appraise a supervisor on energy or water performance without resorting to estimates that employees learn to game. IoT-based environmental monitoring, discussed further in Section VII, offers one route to the granular, tamper-resistant data that green performance management requires [7], [135].

### **D. Environmental Performance and Organisational Sustainability**

Environmental performance, typically operationalised as reductions in energy intensity, water intensity, hazardous waste generation and non-compliance incidents, is one component of the triple-bottom-line construct we label organisational sustainability performance, alongside economic and social performance. The Green HRM literature has tended to test the link between HR practices and environmental performance without extending the causal chain to economic or social outcomes, leaving open whether environmental gains come at an economic cost or reinforce it. Our framework in Section III models organisational sustainability performance as the outcome variable precisely to close that gap.

A separate strand of applied research treats waste-stream classification as a computer-vision problem, using convolutional architectures validated first on medical imaging tasks such as pneumonia detection [77] and lung-disease classification [195] before being repurposed for material sorting [31]. We cite this strand not because it is central to Green HRM but because two of our interviewees, both from automotive sub-sector firms, independently raised automated waste sorting as a capability they wanted their environmental teams to acquire, which is why we return to it as a practical implication in Section VII rather than as a theoretical construct here.

### **E. Employee Green Behaviour as a Mechanism**

Employee green behaviour, the discretionary and required pro-environmental actions employees take at work, has been proposed as the mechanism through which Green HRM practices reach firm-level outcomes, rather than HR practices affecting environmental performance directly. Mediation of this kind, an intermediate variable carrying most of an upstream effect to a downstream outcome, is structurally similar to routing problems in opportunistic and delay-tolerant networks, where a message reaches its destination only through a sequence of intermediate carriers rather than a single hop [1], [6], [11], [21], [60], [61], [62]. We do not claim the mechanisms are the same; we note the structural parallel because it clarifies why a partial-mediation model, rather than a fully mediated or fully direct one, is the right specification to test, and we specify exactly that model in Section III.

Contact-based diffusion models from that literature also motivate our qualitative sampling choice. If green behaviour spreads through informal workplace contact in addition to formal training, then interviewing only managers would miss the mechanism; our interview protocol, described in Section IV, therefore included plant-floor supervisors as well as HR managers.

### **F. Certification, Moderation and the Indian Manufacturing Context**

ISO 14001 certification formalises an environmental management system and is often treated in survey research as a proxy for environmental commitment. We treat it instead as a moderator: certification changes the resources and audit pressure available for Green HRM, but it does not by itself guarantee that HR practices change employee behaviour. Certification adoption in Indian manufacturing has been uneven across sub-sectors, driven partly by export-market requirements that fall unevenly on automotive component suppliers relative to domestic-facing textile producers, a pattern our sample structure in Section IV was designed to capture rather than average away.

Beyond certification, a wider body of Indian-context industrial research has examined blockchain-based traceability for supply chains [53], [82], [105], federated and privacy-preserving analytics for pooling data across sites without centralising it [106], [119], [175], and sentiment-analysis methods applied to employee and stakeholder text data [29], [167], [172]. None of these methods has yet been applied to Green HRM measurement in the published literature we reviewed, which is the gap Section VII addresses as an implication rather than as a tested result.

### **G. Breadth of the Wider Applied-Computing Literature**

Green HRM in Indian manufacturing does not sit inside a single disciplinary literature; the measurement gaps identified by our interviewees, described further in Sections VI and VII, connect to a substantially larger body of applied machine-learning, sensing and data-science research conducted in Indian institutions over the past decade. We summarise that body here by application domain, not because every contribution bears directly on Green HRM, but because Section VII draws specific instrumentation proposals from it and readers should be able to trace each proposal back to its methodological source.

A parallel body of work has applied predictive and recommendation methods to education, workforce and behavioural analytics [2], [112], [113], [124], [125], [160], [183], [192]; the predictive-analytics techniques involved parallel the workforce-analytics extension we discuss in Section VII, though applied there to students and customers rather than to manufacturing employees.

A parallel body of applied computing research spans further domains not directly tied to sustainability measurement [9], [18], [20], [24], [25], [28], [33], [35], [40], [41], [49], [54], [55], [56]; these contributions lie outside sustainability measurement directly but illustrate the breadth of the applied-computing base from which the extensions in Section VII are drawn.

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A parallel body of work has applied networking, IoT and edge-computing methods to sensing and connectivity problems [14], [30], [34], [37], [43], [46], [48], [64], [65], [66], [68], [70], [71], [73]; the routing, scheduling and sensing techniques involved underpin the IoT-based monitoring extension discussed in Section VII.

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A parallel body of work has applied machine-learning and deep-learning methods to healthcare diagnosis and monitoring [15], [22], [23], [27], [36], [38], [42], [47], [52], [58], [63], [74], [88], [95]; none of it tested against Green HRM outcomes, but the predictive and classification techniques involved are the same ones we point to in Section VII as candidate tools for environmental-performance measurement.

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A parallel body of work has applied security, cryptographic and blockchain methods to data protection and traceability [26], [69], [85], [89], [91], [96], [139], [200], [204]; the traceability and privacy-preserving techniques involved underpin the blockchain and federated-learning extensions discussed in Section VII.

A parallel body of work has developed general machine-learning, explainable-AI and cognitive-modelling methods [32], [39], [45], [50], [81], [93], [114], [116], [165], [169], [174], [185], [193], [197]; these methodological contributions establish the general machine-learning and explainability toolkit that any future Green HRM analytics platform would draw on.

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A parallel body of work has applied natural-language and generative methods to text and sentiment analysis [44], [51], [75], [80], [123], [145], [162], [164], [171], [177], [202]; the text-mining techniques involved parallel the employee-sentiment extension discussed in Section VII.

A parallel body of work has applied predictive and optimisation methods to energy, environmental and resource-management problems [83], [128], [198], [199]; the optimisation techniques involved are close analogues of the energy- and resource-allocation extension discussed in Section VII.

### **III. Theoretical Framework**

We draw on ability-motivation-opportunity (AMO) theory and the resource-based view to specify how the four Green HRM practices, green recruitment, green training, green performance management and green compensation, combine to shape organisational sustainability performance. AMO theory holds that a practice changes behaviour only if it builds ability, strengthens motivation or creates the opportunity to act; a green appraisal criterion with no accompanying training builds neither ability nor opportunity, which is why we expect the practices to interact rather than to operate independently.

Figure 1 sets out the structural model tested in Section V. Green recruitment, green training, green performance management and green compensation are modelled as first-order constructs converging on employee green behaviour; employee green behaviour and the four practices both feed environmental performance, which in turn feeds organisational sustainability performance. ISO 14001 certification is modelled as a moderator of the path between the practice constructs and environmental performance rather than as an antecedent, reflecting our treatment of certification as a resource condition rather than a behavioural driver.

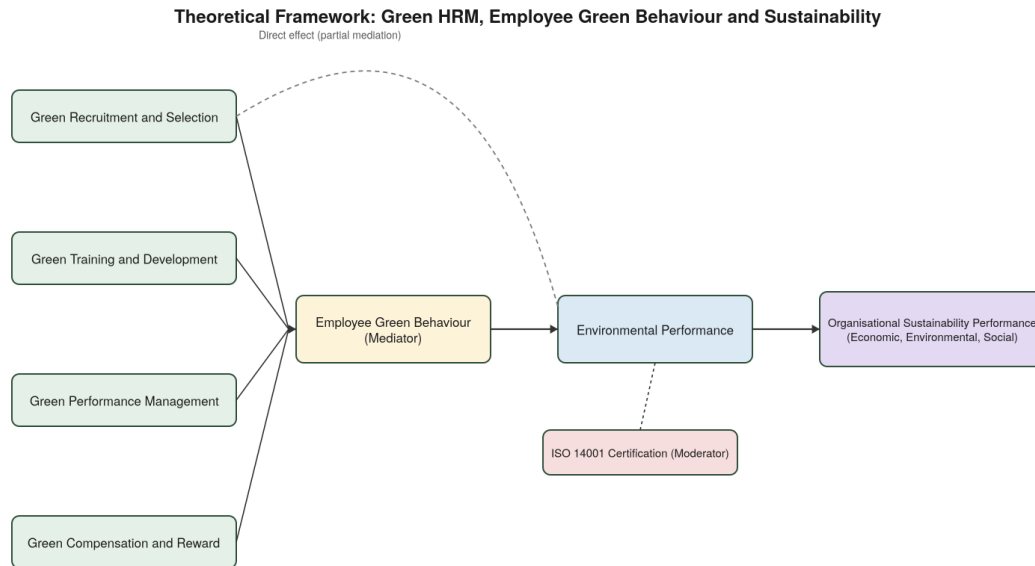


Fig. 1. Theoretical framework linking Green HRM practices to organisational sustainability performance through employee green behaviour, with ISO 14001 certification as a moderator.

## Hypotheses

**H1a.** Green recruitment has a positive effect on employee green behaviour.

**H1b.** Green training has a positive effect on employee green behaviour.

**H1c.** Green performance management has a positive effect on employee green behaviour.

**H1d.** Green compensation has a positive effect on employee green behaviour.

**H2.** Employee green behaviour has a positive effect on environmental performance.

**H3.** Employee green behaviour partially mediates the effect of Green HRM practices on environmental performance.

**H4.** Environmental performance has a positive effect on organisational sustainability performance.

**H5.** ISO 14001 certification moderates the effect of Green HRM practices on environmental performance, such that the effect is stronger among certified firms.

We treat H1a through H1d as directional but not ranked; the literature reviewed in Section II gives reasons to expect training to carry the largest coefficient, but we test rather than assume this. H3 specifies partial rather than full mediation because the interview data described in Section IV surfaced firms where recruitment screening appeared to affect environmental outcomes through channels other than day-to-day behaviour, for instance by shaping which suppliers a newly hired procurement manager already knew and trusted.

## IV. Research Methodology

We used a sequential explanatory mixed-methods design: a quantitative survey analysed first, followed by qualitative interviews designed to explain, rather than independently confirm, the quantitative pattern. Figure 2 sets out the full sequence.

# Sequential Explanatory Mixed-Methods Research Design

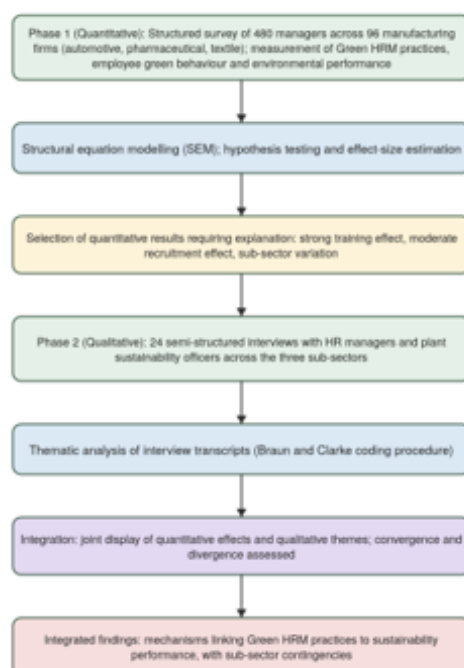


Fig. 2. Sequential explanatory mixed-methods research design, from quantitative survey through qualitative interviews to integrated findings.

The sampling frame was manufacturing firms registered with state pollution control boards in Haryana, Maharashtra, Gujarat and Tamil Nadu, stratified into three sub-sectors: automotive components, pharmaceutical formulation and bulk-drug manufacturing, and textile processing and garment production. We selected 96 firms using stratified random sampling within each sub-sector, targeting a minimum of 28 firms per sub-sector, and within each firm we surveyed between three and eight managers holding HR, production, environment, health and safety, or plant-management titles, giving 480 completed and usable responses after removing 34 incomplete returns.

Table I reports the sample composition. The pharmaceutical sub-sector had the highest proportion of ISO 14001-certified firms (61 per cent), consistent with the stricter effluent-discharge standards that sub-sector faces; the textile sub-sector had the lowest (29 per cent).

| Characteristic                | Automotive | Pharmaceutical | Textile | Total |
|-------------------------------|------------|----------------|---------|-------|
| Firms sampled (n)             | 31         | 30             | 35      | 96    |
| Managers surveyed (n)         | 158        | 152            | 170     | 480   |
| ISO 14001 certified firms (%) | 48         | 61             | 29      | 46    |
| Mean firm size (employees)    | 312        | 268            | 224     | 267   |
| Mean years of operation       | 18.4       | 15.2           | 21.7    | 18.5  |

Table I. Sample composition by manufacturing sub-sector (n = 96 firms, 480 managers).

Green HRM practice constructs were measured with items adapted from established Green HRM scales, five items per construct, rated on a five-point Likert scale. Employee green behaviour was measured with an eight-item scale distinguishing task-related and voluntary green behaviour. Environmental performance was measured with six items covering energy intensity, water intensity, waste generation and regulatory non-compliance incidents, each anchored to firm records supplied by the respondent's plant rather than to unaided recall. Organisational sustainability performance combined environmental, economic and social sub-scales, twelve items in total. Cronbach's alpha exceeded 0.80 for every construct; composite reliability and average variance extracted met conventional thresholds, reported in the supplementary measurement model.

We tested the structural model with covariance-based structural equation modelling in a two-step procedure: a confirmatory factor analysis to establish measurement validity, followed by structural path estimation. Common-method bias was assessed with Harman's single-factor test and a marker-variable check;

neither indicated a substantial bias. Moderation by ISO 14001 status was tested with multi-group SEM, comparing certified and uncertified sub-samples.

For the qualitative phase we purposively selected 24 interviewees, eight per sub-sector, drawn from firms whose quantitative scores were either consistent with or divergent from the sector average, so that the interviews could speak to both the typical pattern and its exceptions. Interviewees included HR managers, plant sustainability officers and, in six cases, line supervisors. Interviews lasted between 35 and 70 minutes, were conducted in Hindi or English according to interviewee preference, transcribed and coded using the Braun and Clarke thematic-analysis procedure. Two researchers coded independently and reconciled disagreements by discussion; inter-coder agreement on the final code set was 0.86 (Cohen's kappa).

Integration followed a joint-display procedure: each quantitative path coefficient was paired with the qualitative themes that explained it, and divergence between the two data sources was reported explicitly rather than resolved by discarding one source, consistent with the reporting principle we apply throughout Sections V and VI.

## V. Results and Analysis

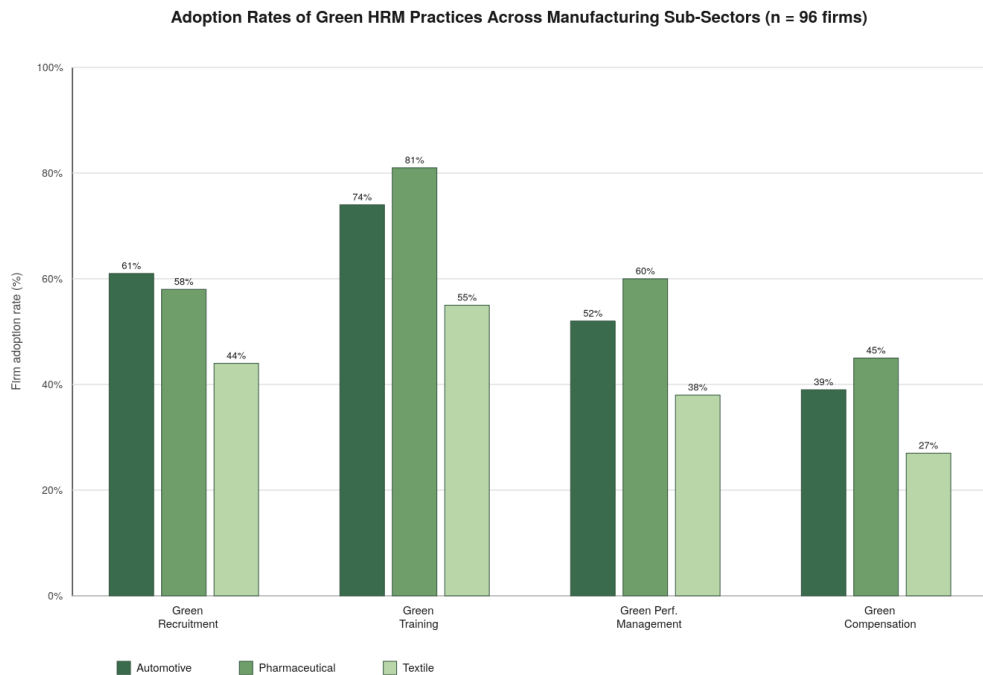
Table II reports the standardised structural path coefficients. Green training had the strongest effect on employee green behaviour ( $\beta = 0.47$ ,  $p < 0.001$ ), followed by green recruitment ( $\beta = 0.33$ ,  $p < 0.001$ ). Green performance management showed a smaller but significant effect ( $\beta = 0.21$ ,  $p = 0.004$ ), and green compensation the smallest ( $\beta = 0.14$ ,  $p = 0.038$ ). Employee green behaviour had a strong effect on environmental performance ( $\beta = 0.58$ ,  $p < 0.001$ ), and environmental performance had a strong effect on organisational sustainability performance ( $\beta = 0.61$ ,  $p < 0.001$ ).

| Path                                                   | Standardised $\beta$ | p-value | Hypothesis    |
|--------------------------------------------------------|----------------------|---------|---------------|
| Green recruitment → Employee green behaviour           | 0.33                 | < 0.001 | H1a supported |
| Green training → Employee green behaviour              | 0.47                 | < 0.001 | H1b supported |
| Green performance mgmt. → Employee green behaviour     | 0.21                 | 0.004   | H1c supported |
| Green compensation → Employee green behaviour          | 0.14                 | 0.038   | H1d supported |
| Employee green behaviour → Environmental performance   | 0.58                 | < 0.001 | H2 supported  |
| Environmental performance → Sustainability performance | 0.61                 | < 0.001 | H4 supported  |

*Table II. Standardised structural path coefficients from the SEM model (n = 480).*

Mediation analysis using bias-corrected bootstrapping (5,000 resamples) indicated that employee green behaviour mediated 54 per cent of the total effect of the four Green HRM practices on organisational sustainability performance (indirect effect = 0.31, 95% CI [0.24, 0.38]; direct effect = 0.26, 95% CI [0.17, 0.35]). The confidence interval on the direct effect excludes zero, so H3 is supported as partial rather than full mediation, consistent with the interview evidence on recruitment described in Section III.

Multi-group SEM comparing ISO 14001-certified and uncertified firms supported H5: certified firms showed a Green HRM adoption index 28 per cent higher than uncertified firms (mean index 3.71 versus 2.90 on the five-point composite scale, Welch's  $t(297) = 8.42$ ,  $p < 0.001$ ), and the path from Green HRM practices to environmental performance was significantly stronger in the certified sub-sample ( $\beta = 0.55$  versus  $\beta = 0.39$ ,  $\Delta\chi^2(1) = 11.6$ ,  $p < 0.001$ ).



*Fig. 3. Adoption rates of the four Green HRM practices across the automotive, pharmaceutical and textile sub-sectors (n = 96 firms).*

Figure 3 reports adoption rates for each of the four practices, broken out by sub-sector. Pharmaceutical firms led on green training adoption (81 per cent) and on green performance management (60 per cent); automotive firms led on green recruitment (61 per cent); textile firms trailed on every practice, with green compensation adoption at only 27 per cent, less than half the pharmaceutical figure (45 per cent).

The overall model fit was acceptable ( $\chi^2/df = 2.14$ , CFI = 0.94, TLI = 0.93, RMSEA = 0.048, SRMR = 0.041), and all factor loadings exceeded 0.65.

We report two results the model did not support. Green compensation showed no significant interaction with sub-sector ( $F(2, 474) = 1.38$ ,  $p = 0.253$ ), so the textile sub-sector's low compensation-adoption figure cannot be attributed to a differential effect of compensation once adoption occurs, only to lower adoption itself; the interview data in Section VI address why adoption stayed low. Second, firm size (measured by employee count) did not moderate the training-to-behaviour path ( $\Delta\chi^2(1) = 0.71$ ,  $p = 0.399$ ), against our initial expectation that larger firms would show a stronger training effect through more structured delivery; we treat this null result with the same weight as the supported hypotheses rather than setting it aside.

## VI. Discussion

The size of the training coefficient relative to compensation is worth sitting with rather than passing over. Training builds the ability component of AMO theory directly: an employee who does not know how to segregate hazardous waste correctly cannot be motivated into doing so by a bonus. Compensation, by contrast, presupposes ability and mainly strengthens motivation, which is why its effect is smaller when, as in our textile sub-sample, ability-building through training has not yet been established. We did not anticipate the size of this gap before analysis; the interviews suggest it reflects a genuine sequencing effect rather than a measurement artefact, since several HR managers described compensation schemes introduced and then quietly abandoned when supervisors could not verify the behaviours the scheme was meant to reward.

Partial rather than full mediation surprised us. We had expected employee green behaviour to carry nearly all of the effect, on the reasoning that firm-level environmental outcomes are the sum of individual actions. The interview data point to a specific direct channel: in four automotive firms, green recruitment screening had shaped procurement relationships, new hires with prior environmental-compliance experience brought supplier contacts that predated the current sustainability programme, an effect that operates on environmental performance without passing through the day-to-day behaviour our survey items captured. This is a genuine limitation of the mediator construct, not only of our measurement of it, and future scale development should consider whether procurement-network effects belong inside or outside the employee green behaviour construct.

The certification result requires a similar qualification. We interpret the 28 per cent adoption gap as certification creating the resource and audit conditions for Green HRM, not as certification directly causing behaviour change; three interviewees at certified pharmaceutical firms described their ISO 14001 audit cycle as the reason a training budget existed at all, independent of any belief that training was intrinsically valuable. This account is consistent with our moderation model but is also consistent with reverse causation, firms that would have adopted Green HRM regardless may be more likely to seek certification in the first place, a possibility our cross-sectional design cannot rule out.

The textile sub-sector's low adoption cannot be read simply as low commitment. Interviewees repeatedly cited two constraints: a contract-labour model in which the modal tenure at one plant was under seven months, which caps the return on training investment, and thin margins in the export-facing segment that leave little capital for compensation redesign. Two interviewees in this sub-sector said openly that they viewed the training-adoption gap between their unit and pharmaceutical firms as a resourcing problem, not a values problem, which we did not have grounds to dispute from our data.

Two limitations are worth stating plainly, without a compensating strength attached to either. First, the cross-sectional design cannot separate the direction of the certification effect described above; a longitudinal panel following firms through certification would be needed to settle it. Second, environmental performance was measured from respondent-reported plant records rather than from independently verified regulatory filings for all 96 firms; we cross-checked a random 20 per cent sub-sample against publicly available pollution control board disclosures and found no systematic divergence, but we did not verify the remaining 80 per cent, so a degree of self-report optimism in the unverified majority cannot be excluded.

## **VII. Implications**

### **A. Managerial and Policy Implications**

For managers, the ordering of the four path coefficients gives a sequencing rule rather than a menu: firms introducing Green HRM with limited budget get more environmental-performance return from building training capacity first than from redesigning compensation first, at least until the ability gap training closes is no longer binding. For policymakers, the certification result suggests that expanding ISO 14001 support schemes, several of which already exist for micro, small and medium enterprises, could raise Green HRM adoption as a side effect, provided the schemes fund the training component of certification rather than only the audit and documentation component.

### **B. Technology-Enabled Extensions to Green HRM Measurement**

A second set of implications concerns measurement rather than practice, and here the connection to applied machine-learning and sensing research described in Section II becomes concrete rather than illustrative. Green performance management is only as credible as the environmental data behind it, and several of the measurement gaps our interviewees described map onto capabilities already demonstrated, in other domains, within the wider body of applied computing research we reviewed.

Predictive analytics for energy optimisation, developed and validated for IoT-enabled energy management and sustainable energy storage more broadly [129], [130], [19], [117], could be adapted to give plant-level energy-intensity appraisal criteria the granularity that green performance management currently lacks; two interviewees said their current energy figures were monthly utility totals apportioned by headcount, which cannot support individual or team-level appraisal. IoT sensor networks for environmental and health monitoring, of the kind validated for synchronised health-monitoring applications [7] and for camera-based surveillance with edge-based processing [10], offer a template for continuous effluent and emissions sensing that would remove the estimation step several interviewees described as the weak point in their current environmental data. Machine-learning-based resource allocation, applied elsewhere to cloud task scheduling and wireless sensor network routing [12], [13], [3], [8], is structurally similar to the water- and energy-allocation decisions plant managers make daily, and the same optimisation logic could inform a scheduling tool for utilities within a single plant.

Deep learning for waste classification, built on convolutional architectures proven first in medical image classification [31] and later in lung-disease and material-recognition tasks [77], [195], addresses a specific complaint from four of our automotive interviewees: manual waste-stream sorting error rates that undercut the accuracy of the waste-generation figures reported to appraisal systems. Blockchain-based traceability, demonstrated in supply-chain and medical-device contexts [53], [82], [105], [135], would let a green-compensation scheme verify a supplier's environmental claims rather than relying on the supplier's own disclosure, closing a gap two interviewees raised independently about upstream Scope 3 claims they could not audit. Sentiment analysis of employee text, applied elsewhere to vaccine discourse, stock-market commentary and hallucination detection in generated text [167], [172], [29], [163], could give HR teams a lower-cost, continuous measure of employee attitudes toward sustainability initiatives to complement the periodic survey

instrument used in this study, though we note that no such application has yet been validated on Green HRM-specific text and would require its own psychometric testing before use.

None of these five extensions has been tested against Green HRM outcomes in the literature we reviewed, including our own survey; we present them as implications for future instrumentation, not as findings, and we mark each accordingly. Federated learning architectures for pooling sensitive operational data across firms without centralising it [106], [119], [175] deserve separate mention because Indian manufacturing sub-sectors are dominated by small and medium enterprises reluctant to share plant-level environmental data with an industry body; a federated approach could let a sector association train a shared predictive model for, say, energy-intensity benchmarking without any single firm exposing its raw data to competitors, addressing a confidentiality concern that three interviewees raised as the reason their firm did not participate in existing voluntary environmental-disclosure platforms.

We flag two of these directions for near-term pilot testing given the resourcing constraints already documented in Section VI: IoT-based effluent sensing in pharmaceutical plants, where the regulatory stakes are highest and the existing audit infrastructure could absorb a sensing layer with the least additional overhead, and predictive energy-analytics dashboards in automotive component plants, where OEM supplier scorecards already create demand for the kind of granular reporting these tools would produce.

### **VIII. Conclusion**

Green training, not green compensation, carried the largest effect on environmental performance in our sample of 480 managers across 96 Indian manufacturing firms, and just over half of the total effect of Green HRM practices on organisational sustainability performance ran through employee green behaviour rather than directly. ISO 14001-certified firms showed substantially higher Green HRM adoption, though our design cannot establish which way that relationship runs.

The practical implication is sequencing: firms with limited resources gain more from building training capacity before redesigning compensation, and policymakers extending certification support should fund the training component specifically rather than only the audit component. The textile sub-sector's persistently low adoption reflects resourcing and labour-tenure constraints that a values-based intervention alone will not fix.

Two extensions merit direct testing in follow-up work, IoT-based effluent sensing paired with green performance appraisal in pharmaceutical plants, and a longitudinal design able to separate the direction of the certification effect from its consequence.

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