

HRM VARIABLE: PERCEIVED ALGORITHMIC FAIRNESS IN AI-ASSISTED PROMOTION DECISIONS → OUTCOME:
ORGANISATIONAL JUSTICE AND DISCRETIONARY EFFORT

PERCEIVED ALGORITHMIC FAIRNESS IN AI-ASSISTED PROMOTION DECISIONS, ORGANISATIONAL JUSTICE AND DISCRETIONARY EFFORT: A COMPARATIVE ANALYSIS OF PRIVATE, GOVERNMENT AND MSME SECTORS

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ABSTRACT

Purpose – Artificial intelligence (AI) is moving from recruitment into the most sensitive gateway of an employee's career: promotion. Existing research on algorithmic fairness treats "the organisation" as a single, undifferentiated context, and draws almost exclusively on Western, large-firm or platform samples. This article asks whether the same AI-assisted promotion system produces the same justice perceptions and the same discretionary effort in a private corporation, a government department and a micro, small or medium enterprise (MSME).

Design/methodology/approach – A structured integrative review of organisational-justice, algorithmic-fairness, public-management and small-firm HRM literatures is combined with a comparative sector analysis built on documented examples: IBM's AI-supported pay-and-promotion workflow (private), India's SPARROW e-APAR and Departmental Promotion Committee system (government), and the Udyam-registered MSME base of 7.83 crore enterprises (MSME). Five propositions and an illustrative simulation are developed.

Findings – The fairness → justice → effort chain is universal, but its weakest link differs by sector. In large private firms the binding constraint is informational justice (explaining a model score); in government it is procedural justice under rule codification, where AI threatens the seniority-cum-merit settlement rather than accuracy; in MSMEs it is interpersonal justice, because an off-the-shelf algorithm interrupts a personal owner–employee exchange. Sector therefore moderates both the fairness → justice path and the justice → discretionary effort slope, which is predicted to be steepest in MSMEs and flattest in government.

Originality/value – The article is, to the author's knowledge, the first to compare AI-assisted promotion fairness across the private–public–MSME triad, and supplies a sector-specific governance agenda for India, where neither the DPDP Act 2023 nor service rules contain an AI-promotion-specific safeguard.

KEYWORDS: Algorithmic Fairness; AI-Assisted Promotion; Organisational Justice; Discretionary Effort; Organisational Citizenship Behaviour; Public Sector HRM; MSME; India

1. INTRODUCTION

Promotion is the decision through which an organisation tells an employee what it believes the employee is worth. It allocates pay, status, authority and future opportunity at once, which is why promotion outcomes have long been among the strongest triggers of justice judgements at work (Greenberg, 1990; Colquitt et al., 2001). When an algorithm enters that decision – ranking candidates, predicting "potential", or flagging who is eligible – the employee's question changes from "Did my manager treat me fairly?" to "Did the system treat me fairly, and is anyone answerable for it?" (Lee, 2018; Newman et al., 2020).

The organisational setting in which that question is asked matters enormously, yet the literature has largely ignored it. Consider three employees in Bengaluru on the same morning. **Ananya**, a senior analyst at a multinational technology firm, opens her promotion dashboard and sees that an AI "readiness score" has placed her in the second quartile; her manager tells her the score is "one input among several". **Ramesh**, a Section Officer in a central government department, knows his promotion to Under Secretary depends on his last five APAR gradings – now recorded online on SPARROW – and on the Departmental Promotion Committee (DPC) benchmark; he worries less about an algorithm than about whether digitisation will quietly shift weight from seniority to scores. **Salma**, a quality supervisor in a 45-person precision-engineering MSME in Peenya, learns that the owner has subscribed to a low-cost HR software package that

“suggests” who should become shift-in-charge; until last year the owner simply decided, after talking to the floor. All three are experiencing AI-assisted promotion. They are not experiencing the same thing.

This article is a sector-comparative companion to the author’s earlier analysis of the same variable pairing framed on India-versus-foreign implementation (Sastry, 2026c). It asks three research questions. **RQ1:** Which dimension of organisational justice is most exposed when AI is introduced into promotion decisions in private, government and MSME settings? **RQ2:** Does sector moderate the pathway from perceived algorithmic fairness through organisational justice to discretionary effort? **RQ3:** What sector-specific governance designs follow for India, where AI-assisted promotion is spreading faster than the rules that govern it?

The contribution is threefold. First, it imports the classic public–private distinction (Rainey & Bozeman, 2000; Boyne, 2002) and the small-firm HRM literature (Cardon & Stevens, 2004) into algorithmic-fairness research, which Starke et al. (2022) show remains context-thin and almost exclusively Western. Second, it uses concrete, documented examples rather than abstract sector labels. Third, it converts the comparison into five testable propositions and a research agenda.

2. REVIEW OF LITERATURE

2.1 Organisational justice and the promotion decision

Organisational justice research distinguishes four dimensions (Colquitt, 2001). **Distributive justice** concerns whether the outcome matches contribution, rooted in equity theory (Adams, 1965). **Procedural justice** concerns the process: consistency, bias suppression, accuracy, correctability, representation and ethicality (Leventhal, 1980), together with voice and process control (Thibaut & Walker, 1975). **Interpersonal justice** concerns dignity and respect in how the decision is communicated, and **informational justice** concerns the adequacy and candour of explanations (Bies & Moag, 1986). Meta-analytic evidence shows each dimension predicts distinct outcomes, with procedural justice most strongly linked to evaluations of the system and interpersonal justice to evaluations of the decision-maker (Colquitt et al., 2001). Promotion is the HR decision in which all four dimensions are activated simultaneously. Earlier work by the author on Indian employees found that the perceived quality of performance appraisal – the input to promotion – significantly shapes engagement (Sastry & Selvarasu, 2014), and that how departments structure task responsibilities shapes whether achievement is visible enough to be rewarded at all (Sastry, 2024). Both findings imply that a promotion algorithm inherits whatever visibility and appraisal biases already exist in its training data.

2.2 Perceived algorithmic fairness

Lee (2018) showed experimentally that people judge algorithmic and human decisions similarly for mechanical tasks, but view algorithmic decisions as less fair for tasks requiring human skills such as evaluation, because algorithms are seen to lack intuition and the capacity for subjective judgement. Newman et al. (2020) extended this to HR decisions, finding that algorithmic evaluations are perceived as less fair because they appear to reduce people to quantifiable metrics – a “reductionism” perception that is directly relevant to promotion, where employees believe their contribution exceeds what is measured. Ötting and Maier (2018) showed that procedural justice matters as much when the decision agent is an intelligent system as when it is a human, and Jabagi et al. (2024), surveying 435 Uber drivers, found that perceived fairness of algorithmic evaluation decisions is positively related to job satisfaction and perceived organisational support. Starke et al.’s (2022) systematic review of 58 empirical studies, however, highlights that this evidence is heterogeneous in its concepts and drawn almost entirely from Western-democratic contexts. The author’s own work on AI-analytics in hiring shows that Indian HR functions adopt algorithmic tools quickly but govern them unevenly (Sastry & Mallya, 2025a), and that transparency about an algorithm’s existence does not by itself produce trust unless employees can understand and contest it (Sastry, 2026a).

2.3 Discretionary effort and social exchange

Discretionary effort – behaviour above formal role requirements, captured in organisational citizenship behaviour (OCB) directed at individuals (OCB-I) and at the organisation (OCB-O) – is “not directly or explicitly recognised by the formal reward system” (Organ, 1988). Social exchange theory explains why justice drives it: employees who feel fairly treated reciprocate with effort they are not obliged to give (Blau, 1964; Cropanzano & Mitchell, 2005). Discretionary effort is therefore the most sensitive behavioural indicator of whether an AI-assisted promotion is perceived as just, because it is the effort employees can withdraw without sanction.

The author’s research on delegation shows that Indian employees respond to autonomy and resources with initiative beyond their role (Sastry & Ravish, 2025), and that designations function as social-comparison signals with economic consequences for organisational growth (Sastry, 2025a). If an algorithm allocates designations, then the social-comparison signal is now sent by a system, and the reciprocity norm that sustains discretionary effort must attach to a non-human decision-maker.

2.4 Sector differences: the publicness of the promotion decision

Public and private organisations differ in goals, constraints and employee motivation (Rainey & Bozeman, 2000). Boyne's (2002) review found public organisations more bureaucratic, with managers less materialistic and with weaker organisational commitment, while Perry and Wise (1990) argued that public employees are partly motivated by public service motivation (PSM) rather than by extrinsic rewards. For promotion, this means the government employee's discretionary effort is less contingent on promotion outcomes and more on mission and job security. In India, central government promotion is codified: APAR gradings feed DPC benchmarks under seniority-cum-merit or selection rules. The SPARROW online APAR system was launched for IAS officers from 1 April 2014 and has since been extended across central services and central public sector enterprises (DoPT, 2015; DPE, n.d.). SPARROW is digitisation, not prediction; but it creates the structured data on which AI-assisted promotion could later be built.

Globally, the OECD's (2025) analysis of 200 public-sector AI use cases found adoption lagging in civil-service management relative to public-service delivery. The author's Human-in-the-Loop analysis argues that public-law contestability rules make human review legally load-bearing in public employment in a way that private employment-at-will regimes do not (Sastry, 2026b), and work on departmental structure shows that rigid hierarchies reduce the visibility of individual achievement (Sastry, 2024).

2.5 HRM and promotion in MSMEs

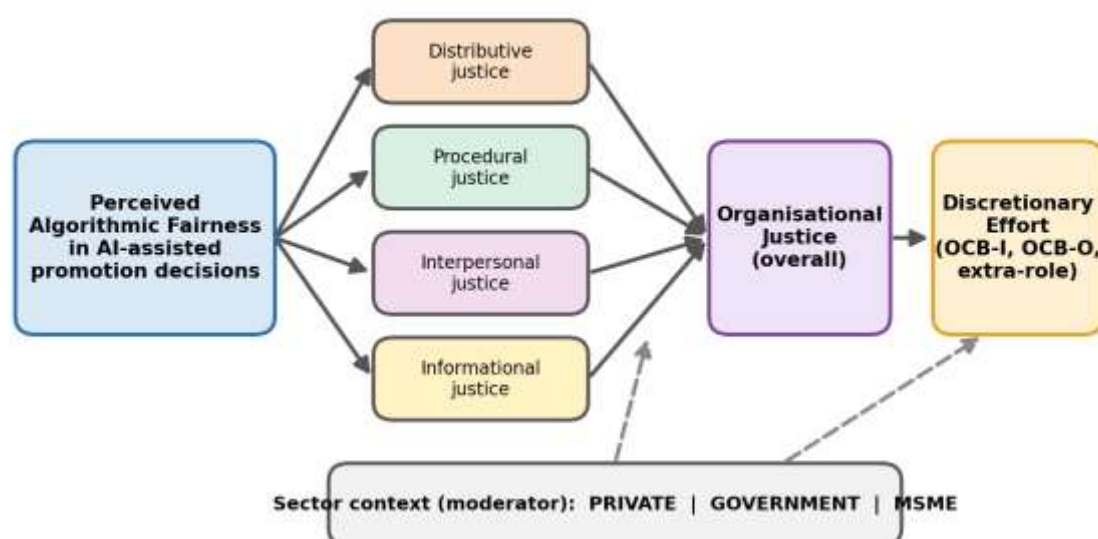
Small firms manage people informally, through the owner, with few written policies and close personal relationships (Cardon & Stevens, 2004). Promotion in an MSME is typically a personal decision embedded in a long relational exchange; its legitimacy rests on the owner's perceived integrity rather than on a procedure. India's MSME base is vast: 7.83 crore enterprises had registered on the Udyam and Udyam Assist platforms by February 2026, reporting 34.50 crore jobs, and Udyam-reported employment rose from 5.45 crore in FY2023-24 to 8.04 crore in FY2025-26 (Ministry of MSME, 2026).

The author's work on Bengaluru IT start-ups operating under MSME frameworks found that women employees perceive promotion pathways as opaque and dependent on founder discretion (Sastry & Mallya, 2025b), and work on women micro-entrepreneurs in Karnataka documents the resource constraints that prevent small enterprises from investing in formal HR systems (Sastry, 2025b). When such firms adopt AI, they adopt it off the shelf, without the internal capability to audit it.

2.6 Research gap

Three gaps follow. **Gap 1 (context):** algorithmic-fairness studies treat the organisation as context-free; none compares the private, government and MSME sectors. **Gap 2 (mechanism):** studies test fairness → attitudes (satisfaction, trust) but rarely carry the chain through to discretionary effort. **Gap 3 (geography):** India – with the world's largest government workforce digitisation programme alongside one of the largest MSME bases – is almost absent from the evidence base. Figure 1 presents the conceptual model that addresses these gaps.

Figure 1. Conceptual model: fairness → justice → discretionary effort, moderated by sector



Source: Author's conceptualisation.

3. METHODOLOGY

The study uses a **structured integrative review** combined with a **comparative sector-case analysis**. It is not a PRISMA systematic review; the purpose is theory-building across literatures that rarely cite each other. Sources were drawn from four streams: organisational-justice theory, algorithmic-fairness research, public-private comparison, and small-firm HRM, supplemented by official Indian documents (DoPT and DPE APAR guidelines; Ministry of MSME parliamentary data) and international surveys (SHRM, 2024; SHRM, 2026; OECD, 2025). Each sector is illustrated with a documented example and an illustrative vignette; vignettes are composite and are labelled as such. All citations were verified against publisher or official records before drafting. The analysis proceeds in three steps: (i) mapping each sector's promotion architecture (Table 1); (ii) locating, for each sector, the justice dimension most exposed to AI (Tables 2 and 3); and (iii) deriving propositions (Table 4).

4. COMPARATIVE SECTOR ANALYSIS WITH EXAMPLES

Table 1 summarises how promotion is decided in each sector and what AI changes. The differences are not of degree only; they concern who the decision-maker is, what legitimises the decision and what remedy the employee has.

Table 1. Promotion architecture and AI exposure: Private vs Government vs MSME

Feature	Private (large firm)	Government (India)	MSME
Basis of promotion	Performance + potential; manager calibration	Seniority-cum-merit / selection; APAR benchmark; DPC	Owner's judgement; loyalty and versatility
Current AI role	Readiness/potential scores, eligibility flags (e.g. IBM)	Digitised APAR (SPARROW); no predictive scoring yet	Off-the-shelf HRMS "suggestions"; often none
Source of legitimacy	Meritocracy and market competitiveness	Rule, neutrality, equal treatment	Owner's personal integrity
Remedy for employee	Internal grievance; exit to labour market	Representation against APAR; CAT/courts	Informal appeal to owner; exit
Data available to train AI	Rich, multi-year HRIS data	Structured but narrow APAR grades	Sparse, unrecorded
Most exposed justice dimension	Informational	Procedural	Interpersonal
Discretionary-effort sensitivity	Moderate-high	Low-moderate (PSM, tenure)	High (personal exchange)

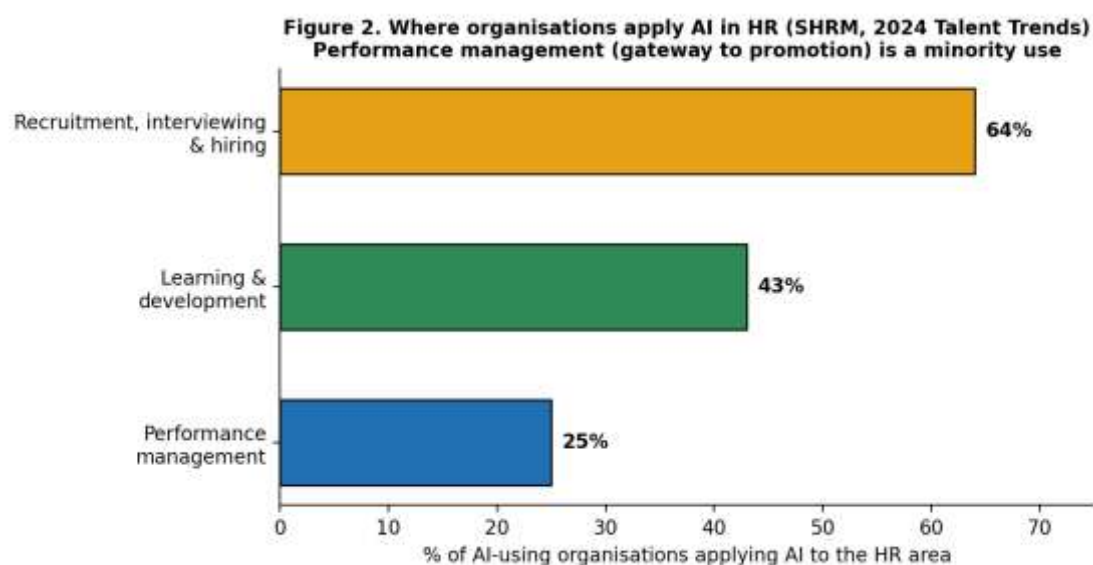
Source: Author's synthesis from Rainey & Bozeman (2000), Boyne (2002), Cardon & Stevens (2004), DoPT (2015), DPE (n.d.) and the examples in Section 4.

4.1 Private sector: the explanation problem

Documented example – IBM. IBM has used Watson analytics to infer employees' future skills from their experience, projects and training, producing an assessment rating that managers consider in bonus, pay and promotion decisions; the company reported a 96 per cent accuracy rate against internal HR-expert analysis (Business Standard, 2018). By 2023 IBM reported using AI in performance evaluation to determine which employees qualify for a raise or promotion, with recommendations sent to managers to cross-check (Fortune, 2023). The design keeps a human in the loop; the employee, however, experiences a prediction of *future* performance they cannot see or dispute.

Illustrative vignette – Indian IT services. In Ananya's firm the readiness score weights client feedback, certifications and utilisation. She has strong client feedback but lower utilisation because she spent a quarter mentoring new joiners – classic OCB-I. The algorithm, trained on outcomes, cannot see mentoring; the result feels distributively unfair, but what actually damages her trust is that no one can tell her *why* she is in the second quartile. Her manager's reply – "the system is objective" – fails the informational-justice test (Bies & Moag, 1986). Her rational response is to stop mentoring. This is the mechanism by which an unexplained promotion algorithm destroys exactly the discretionary effort it cannot measure.

Figure 2 shows why this is the leading edge rather than the norm: even among organisations using AI in HR, performance management – the gateway to promotion – is a minority application, and SHRM reports that large employers lead adoption (SHRM, 2024).



Source: SHRM (2024), Talent Trends Survey: Artificial Intelligence Findings (n = 2,366 HR professionals).

4.2 Government sector: the codification problem

Documented example – SPARROW and the DPC. India's Smart Performance Appraisal Report Recording Online Window (SPARROW) moved APAR filing online from 2014, with e-sign authentication and step-wise workflow, and has been extended to CPSE top management (DPE, n.d.). Departments have since begun linking APAR to iGOT Karmayogi training records. Promotion itself remains a DPC decision applying benchmark gradings to a seniority-ordered zone of consideration. This is a rules-based system in which the decision is legitimate *because* it is codified and predictable.

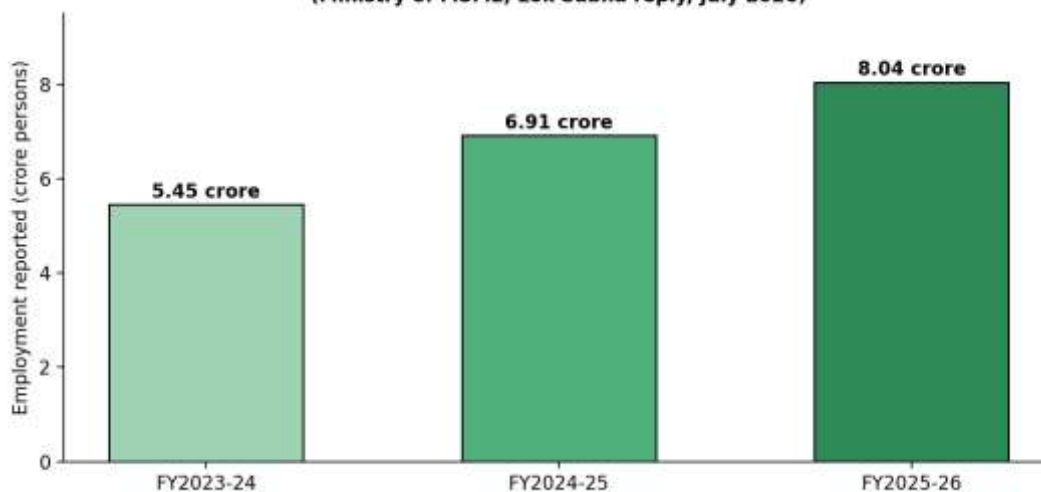
Illustrative vignette – central secretariat. Ramesh does not fear that an algorithm will misjudge him; he fears that it will be introduced at all, because any model that weights scores more heavily than seniority redistributes promotions between cohorts. In government, AI threatens a negotiated procedural settlement – the consistency and representation criteria of Leventhal (1980) – rather than accuracy. Because his job security and PSM are unaffected, his discretionary effort declines only modestly; but collective voice (association representations, litigation before the Central Administrative Tribunal) rises sharply. The OECD (2025) observation that civil-service management lags other functions in AI adoption is consistent with this: the barrier is legitimacy, not technology.

International contrast. Under the EU AI Act, AI systems intended to make or influence decisions affecting promotion are classified as high-risk (Regulation (EU) 2024/1689, Annex III), requiring human oversight and documentation for public and private employers alike. India has no equivalent; the DPDP Act 2023 governs personal data generally but contains no promotion-specific safeguard.

4.3 MSME sector: the relationship problem

Documented context – scale and informality. The MSME sector's scale (Figure 3) means that even marginal AI adoption touches crores of employees. Yet SHRM's survey evidence shows that most small and mid-sized organisations do not use AI in HR at all (SHRM, 2024), and its 2026 survey of 1,908 HR professionals found 54 per cent of organisations had not adopted AI in HR and had no plans to do so that year (SHRM, 2026). MSME AI adoption in promotion is therefore rare, bundled, and largely invisible to regulators.

Figure 3. Employment reported by MSMEs on the Udyam portal, India
(Ministry of MSME, Lok Sabha reply, July 2026)



Source: Ministry of MSME (2026), written reply in the Lok Sabha, 23 July 2026.

Illustrative vignette – Peenya engineering unit. Salma’s owner has never written a promotion policy; promotion was a conversation. When the HR package “suggests” a younger colleague because he logged more overtime in the attendance module, the decision is not obviously wrong, but it is delivered without the conversation. What Salma experiences as unjust is not the outcome but the withdrawal of personal recognition – an interpersonal-justice violation (Bies & Moag, 1986). Because the MSME relationship is the reward system, her discretionary effort (staying late to finish a rush order, training new operators) falls steeply. The owner, who adopted the tool to appear “objective”, loses the very goodwill that kept the small firm agile.

Table 2. Worked examples: the same AI promotion tool in three sectors

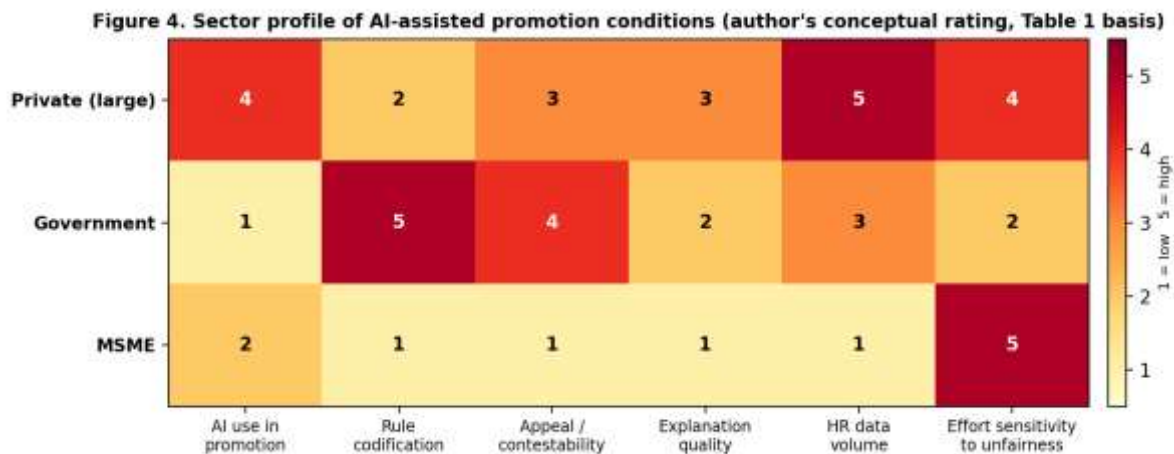
Element	Private – Ananya	Government – Ramesh	MSME – Salma
AI input	Readiness score (utilisation, certifications, feedback)	Digitised APAR grades; proposed score-weighting	HRMS overtime & attendance-based suggestion
What the employee contests	“Why am I in Q2?”	“Why should scores override seniority?”	“Why did the owner not talk to me?”
Justice dimension violated	Informational	Procedural (consistency, representation)	Interpersonal
Discretionary effort withdrawn	Mentoring juniors (OCB-I)	Voluntary committee work (modest)	Rush-order overtime, training others (OCB-I & OCB-O)
Collective response	Low; individual exit	High; association / tribunal	Low; quiet exit
Repair mechanism	Explanations, score access	Rule-making, consultation, human DPC final say	Owner-delivered decision, AI as advisory only

Note: Vignettes are composite illustrations constructed by the author; IBM, SPARROW and Udyam data are documented examples.

Table 3. How each justice dimension manifests under AI-assisted promotion, by sector

Justice dimension	Private	Government	MSME
Distributive	Outcome vs market-referenced merit; pay linked	Outcome vs batch/seniority peers	Outcome vs loyalty and tenure with owner
Procedural	Consistency across managers; model bias audits	Codified rules, representation, legality – dominant	Largely absent; owner discretion was the procedure
Interpersonal	Manager’s delivery of score	Formal, impersonal by design	Personal recognition – dominant
Informational	Explainability of model features – dominant	Reasons recorded in APAR/DPC minutes	Owner unable to explain vendor tool

Figure 4 condenses Tables 1–3 into a sector profile. The private sector combines high AI use with high data volume; government combines high codification with high contestability but low AI use; MSMEs combine low formal structure with the highest sensitivity of effort to perceived unfairness.



Source: Author's conceptual rating derived from Tables 1–3; ratings are not survey estimates.

5. PROPOSITIONS

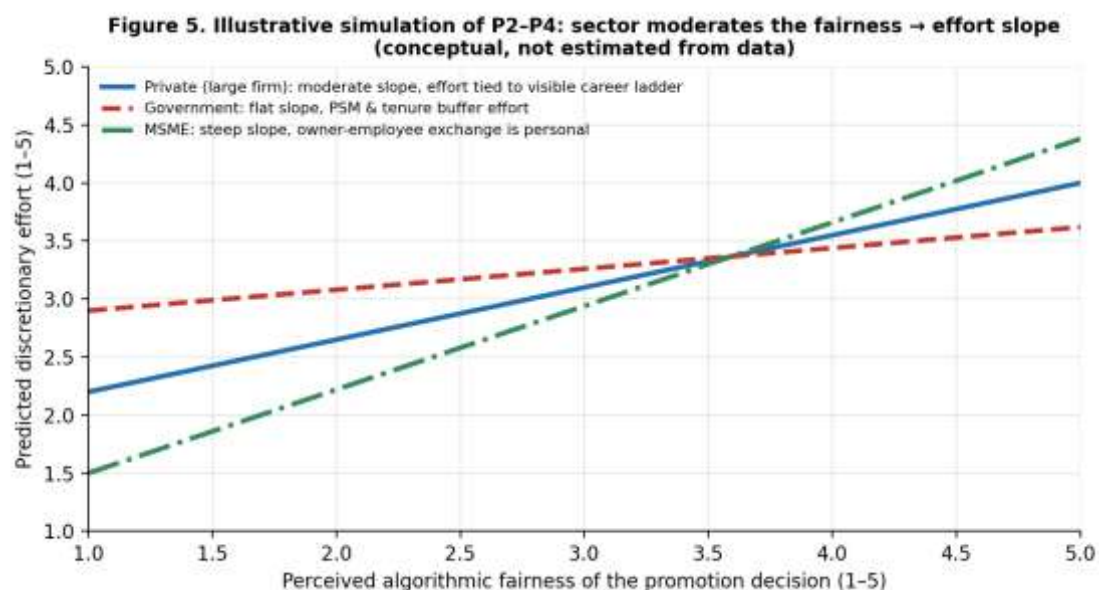
Proposition 1 (core mediation). Perceived algorithmic fairness of AI-assisted promotion decisions is positively related to discretionary effort, and this relationship is mediated by overall organisational justice, in all three sectors.

Proposition 2 (private sector). In large private firms, informational justice is the strongest mediating dimension; providing employees with access to their score and its principal drivers attenuates the negative effect of unfavourable algorithmic outcomes on discretionary effort.

Proposition 3 (government sector). In government organisations, procedural justice – specifically consistency with codified promotion rules and representation in rule change – is the strongest mediating dimension, and the justice → discretionary effort slope is flatter than in other sectors because public service motivation and tenure security buffer effort; the dominant response to perceived unfairness is collective voice rather than effort withdrawal.

Proposition 4 (MSME sector). In MSMEs, interpersonal justice is the strongest mediating dimension; replacing an owner-delivered promotion conversation with an algorithmic suggestion lowers perceived fairness even when the outcome is identical, and the justice → discretionary effort slope is steeper than in other sectors.

Proposition 5 (India governance). In India, the absence of AI-promotion-specific regulation means that sector-level differences in perceived fairness are determined chiefly by organisational design (explanation in private firms, rule-making in government, owner involvement in MSMEs) rather than by legal compliance, unlike EU jurisdictions where Annex III high-risk obligations partially standardise the procedure across sectors.



Source: Author's illustrative simulation of Propositions 2–4; slopes are conceptual and require empirical estimation.

Table 4. Summary of propositions and suggested tests

Prop.	Statement (short)	Key moderator / mediator	Suggested test
P1	Fairness → justice → effort	Overall justice (mediator)	Multi-sector survey; PLS-SEM mediation
P2	Private: informational justice dominant	Score access / explanation	Field experiment on explanation formats
P3	Government: procedural dominant, flat effort slope	PSM, tenure; collective voice	Multi-group SEM; tribunal case analysis
P4	MSME: interpersonal dominant, steep slope	Owner delivery vs AI delivery	Vignette experiment with MSME employees
P5	India: design substitutes for regulation	Jurisdiction (India vs EU)	Cross-national matched-sector comparison

6. DISCUSSION

6.1 Present conditions

At present the three sectors stand at different points. Large private firms are already using AI in promotion pipelines, usually with a manager retaining the final decision, as IBM's practice illustrates. Indian government has digitised the inputs to promotion but not the judgement; SPARROW records, it does not predict. MSMEs largely have not adopted AI in HR, but the spread of low-cost HR software is beginning to embed algorithmic suggestions without any explicit decision to "use AI". The common risk is that each sector imports a fairness solution designed for another: explainability dashboards built for corporations will not repair an MSME's interpersonal breach, and accuracy audits will not answer a government employee's procedural objection.

6.2 Theoretical implications

The analysis extends organisational-justice theory by showing that the *dominant* justice dimension is sector-contingent when the decision-maker is algorithmic. It extends algorithmic-fairness research by treating sector as a moderator and by carrying the chain to discretionary effort rather than stopping at attitudes. It also refines public-private comparison: AI does not merely "arrive later" in government, it threatens a different settlement.

6.3 Managerial and policy implications

Private firms should give employees access to their own promotion score and its principal drivers, record OCB-type contributions (mentoring, knowledge-sharing) as model inputs, and train managers to deliver algorithmic outcomes with reasons. **Government** should treat any move beyond digitisation as a rule change requiring consultation with service associations, keep the DPC as the final decision-maker, and publish the weighting logic as part of recruitment and promotion rules. **MSMEs** should use AI suggestions as advisory only, with the owner delivering the decision personally; industry associations and MSME-DFO clusters could provide shared, audited HR tools. **Policymakers** could issue sector-neutral guidance under the DPDP framework requiring notice, explanation and human review for AI-influenced promotion decisions.

7. Future Research and Innovation Agenda

Table 5. Future research agenda: HR and economics innovations

Direction	Research question	Sector focus	Method
Fairness-by-design	Do score-access dashboards raise informational justice without gaming?	Private	Randomised field experiment
Rule-embedded AI	Can models constrained to seniority-cum-merit rules preserve procedural legitimacy?	Government	Simulation on anonymised APAR data
Shared MSME HR utilities	Do cluster-level audited HR tools reduce interpersonal breach?	MSME	Quasi-experiment across clusters
Economic cost of withdrawn OCB	What is the productivity value of discretionary effort lost to unfair AI promotion?	All	Firm-level panel; production-function estimation
Cross-national comparison	Does EU Annex III compliance equalise fairness across sectors?	All	India-EU matched survey

A particularly important economic question is the cost of discretionary effort withdrawn under unfair AI promotion. Because OCB is unrecorded, its loss is invisible in accounts while its effect – slower onboarding, weaker knowledge transfer, lost goodwill – is real. Estimating this cost by sector would allow organisations to compare the efficiency gains of AI-assisted promotion against the justice-mediated productivity loss.

8. CONCLUSION

AI-assisted promotion is not one phenomenon but three. In private firms it is an explanation problem, in government a codification problem, and in MSMEs a relationship problem. The pathway from perceived algorithmic fairness through organisational justice to discretionary effort holds in each, but the dimension of justice that carries it, and the steepness of the effort response, differ systematically. For India – where a large digitised civil service and a vast MSME base sit alongside a fast-adopting private sector – the lesson is that one generic “AI fairness” standard will not deliver fair promotion. Each sector needs a governance design matched to the source of legitimacy its employees already rely on.

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