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FROM HUMAN RESOURCE MANAGEMENT (HRM) TO ALGORITHMIC GOVERNANCE: THE CHANGING DISCRETION AND ROLE STRAIN OF LINE MANAGERS

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Abstract

Line managers once held wide latitude over hiring, appraisal, scheduling, and discipline. That latitude is narrowing. As organizations adopt algorithmic HR systems, decisions once anchored in supervisory judgment are increasingly pre-structured, scored, or overridden by software. This paper pursues two objectives: first, to examine how algorithmic management and HR algorithms reconfigure the discretionary authority of line managers across core decision domains; second, to analyze the role strain managers experience mediating between algorithmic outputs and the employees who live with their consequences. Drawing on an integrative review of recent empirical and theoretical literature, the paper finds that discretion is not simply removed but redistributed unevenly across recruitment, performance management, and scheduling, producing a manager accountable for outcomes they no longer fully controls. This mismatch generates measurable strain: ambiguity about where authority sits, ethical unease about opaque scoring logic, and a residual burden of explaining decisions the manager did not make. The paper proposes a conceptual pathway linking algorithmic input to discretion compression to role strain, and closes with implications for organizations designing human-AI collaborative HR systems.

Keywords: Algorithmic Management, Line Managers, Managerial Discretion, Role Strain, Algorithmic Governance, Human Resource Management

1. Introduction

A line manager's job used to be built on judgment calls. Who to hire. How to score a review. Whether to let a shift swap slide. Little of that is straightforwardly true anymore. Algorithmic management, understood as the large-scale use of data-driven systems to carry out coordination and control functions once performed by human

supervisors, has moved well beyond the platform economy where it was first documented (Jarrahi et al., 2021). It now sits inside conventional firms, threaded through recruitment software, performance dashboards, and scheduling tools that were sold as efficiency aids and have quietly become decision-makers in their own right (Benlian et al., 2022).

Algorithms do not make decisions. It is that managers remain responsible for decisions the algorithm effectively made. Meijerink and Bondarouk (2021a) call this a duality: algorithmic systems simultaneously restrain and enable managerial autonomy, often within the same workflow. A manager might gain a dashboard that flags underperformance instantly, and lose the room to interpret context before acting on it. Kim et al. (2024) frame this as part of a broader repositioning of strategic HRM, one where technology reshapes what counts as a legitimate managerial decision in the first place.

Much of what is known about algorithmic control comes from gig and platform work, where the worker-facing app is the primary interface of management (Noponen et al., 2023). Less is known about what happens inside ordinary organizations, where a human manager still stands between the system and the employee, absorbing whatever tension that position generates. This gap matters because the line manager is precisely the actor tasked with translating algorithmic output into something an employee can live with, appeal, or trust.

1.1 Statement of the Problem

The problem this paper addresses is a growing mismatch between where decision authority actually sits and where accountability for that decision is still assigned. As algorithmic HR systems take over recruitment scoring, performance dashboards, and scheduling optimization, the substance of managerial judgment is being displaced even though the manager remains the person formally answerable for the outcome and the person an employee turns to when a decision needs explaining or appealing. Existing literature documents each half of this problem separately. One stream, rooted mainly in gig and platform-work research, examines how algorithms control workers directly (Jarrahi et al., 2021; Noponen et al., 2023). A second stream, situated in conventional HRM, treats algorithmic tools primarily as productivity or fairness interventions (Vrontis et al., 2021; Budhwar et al., 2022). None of the streams, on its own, explains what happens to the line manager who sits between the two, retaining formal responsibility while losing much of the interpretive latitude that responsibility once presupposed. Left unexamined, this gap leaves organizations designing human-AI collaborative HR systems with little empirical or conceptual guidance on how discretion loss translates into managerial strain, and with no coherent basis for deciding where human override authority should be preserved. Based on these worries, this paper sets out to bridge the gap.

1.2 Objectives of the Study

This paper addresses two linked objectives:

- i. To examine how algorithmic management and HR algorithms reconfigure the discretionary authority line managers exercise in recruitment, performance evaluation, scheduling, and disciplinary decisions.
- ii. To analyze the role strain managers experience mediating between algorithmic governance systems and the employees those systems govern, and to draw out the implications for HRM practice.

1.3 Research Questions

In line with these objectives, the review is organized around the following research questions:

- i. RQ₁: How do algorithmic management and HR algorithms reconfigure line-manager discretion across recruitment, performance evaluation, scheduling, and disciplinary decisions?
- ii. RQ₂: What forms of role strain do line managers experience as a result of mediating between algorithmic outputs and the employees who live with their consequences, and what mechanism links discretion compression to that strain?

2. Conceptual and Theoretical Framework

2.1 From HRM to Algorithmic Management

Human resource management has always rested on a chain of discretionary judgments, most exercised not by HR departments but by the line managers who supervise people day to day. Algorithmic management disrupts that chain. Parent-Rochelleau and Parker (2021) describe algorithms as work designers in their own right, shaping task allocation, pacing, and evaluation criteria in ways that used to fall squarely within a supervisor's remit. Chen (2026) argues that algorithmic HRM constitutes a distinct mode of algorithmic governance, organized around transparency, fairness, and the residual space left for human agency once the system has done its work. That residual space is this paper's central concern.

The transition is uneven, and probably should be. Vrontis et al. (2021) note that adoption of AI across HRM functions varies by function, sector, and the maturity of an organization's data infrastructure. Recruitment tends to be automated earliest and most thoroughly; discipline stays, for now, more clearly human. Budhwar et al. (2022) point out that this unevenness creates a patchwork of managerial authority, full discretion in some domains and almost none in others, often within the same job description.

2.2 Managerial Discretion in Classical HRM

Discretion, in the classical HRM literature, refers to the latitude a manager has to interpret organizational policy in light of situational knowledge the policy cannot anticipate. Wiblen and Marler (2021) trace how talent decisions were historically distributed between formal systems and informal managerial judgment, with the informal component treated as a corrective to the limits of any formal rule. Automated decision support was already narrowing that corrective role a decade ago. Langer et al. (2020) found that automated systems changed not just the outcome of personnel selection tasks but the means by which managers arrived at a decision, often compressing a multi-step evaluative process into acceptance or rejection of a machine-generated score.

2.3 Algorithmic Governance as a Mode of Organizational Control

Algorithmic governance is best understood as a layer of control sitting above, and increasingly substituting for, direct managerial oversight. Noponen et al.'s (2023) systematic review proposes an Algorithmic Management Grid distinguishing controlling from enabling uses of these systems, finding that organizations have so far leaned heavily toward the controlling end. Weiskopf and Hansen (2022) push this further with the concept of algorithmic governmentality, arguing that people-analytics systems do not just monitor behavior but shape the ethical space within which managers and employees understand acceptable conduct.

Accountability is where this gets complicated. Goldsmith and Yang (2025) examine how algorithmic tools reshape accountability and discretion in public-sector governance, a finding that translates directly into organizational HRM: when a decision is jointly produced by a human and a system, who answers for it becomes genuinely unsettled. Mökander et al. (2021) argue that ethics-based auditing of automated decision systems is

one response, though such auditing remains limited in scope and rarely reaches the line-manager level where the decision is actually delivered.

2.4 Empirical Review

Where Section 2.1 to 2.3 set out the conceptual scaffolding, this section reviews the empirical studies most directly load-bearing for the two research questions, examining what each actually measured or observed rather than the concepts it invoked.

Li et al. (2021), on discretion in recruitment, interviewed practicing recruiters and HR professionals directly and reported that participants felt obligated to defer to algorithmic rankings even when their own judgment pointed elsewhere, since departing from the system required justification the system itself did not demand. Langer et al. (2020), using a controlled personnel-selection task, found automated decision support changed not just outcomes but the means by which managers reached a decision, compressing a multi-step evaluative process into acceptance or rejection of a machine-generated score. Köchling and Wehner (2020), in a systematic review of recruitment algorithms, documented how training-data bias propagates into hiring outcomes in ways individual managers are poorly positioned to detect.

On performance management, Edwards et al. (2024) surveyed employees and distinguished algorithmic HR systems perceived as managerial control from those perceived as feedback provision, finding the same system could land either way depending on the manager's retained interpretive room. Kinowska and Sienkiewicz (2022) surveyed European organizations and found algorithmic management practices correlated with lower workplace wellbeing overall, most strongly where managers had little say over how monitoring data was used. Al Khalidi (2026) linked AI-based workplace surveillance to measured employee calmness and organizational citizenship behavior, with managerial conduct mediating the relationship.

Reviewing scheduling, Liu et al. (2025) studied platform-based teams and found algorithmic management supported team resilience by reducing objectification only where informal leadership remained active alongside the system. Bucher et al. (2020) documented anticipatory compliance among gig workers, a coping pattern in which workers adjust behavior preemptively to satisfy partly opaque algorithmic criteria, a dynamic that reshapes what a manager is actually managing.

Considering role strain, Tandon et al. (2024) interviewed managers directly and found genuine ambivalence rather than uniform hostility toward algorithmic HRM, some describing relief at offloading ethically uncomfortable decisions and others describing a loss of discretionary meaning. Robinson et al. (2025) found, through qualitative fieldwork, managers occupying what they term a limbo position between hierarchical authority and passive conduit for algorithmic instruction. Dima et al. (2024) surveyed the HR triad of managers, employees, and HR professionals and found line managers reporting the least clarity about their own future role. Deepa et al. (2024), reviewing competency requirements, found a widening skills gap in which managers are expected to interpret and defend algorithmic outputs they were never trained to evaluate.

Adias (2025) studied the sectoral and regional variations, documented digital HRM transformation in Nigerian organizations and its measured impacts on talent management and workforce wellbeing, while Owor et al. (2025) systematically reviewed Africa's regulatory and infrastructural preparedness for AI-driven HRM. Taken together, these empirical sources converge on the same pattern the conceptual literature anticipates: discretion loss is uneven across function and geography, and where it occurs, it produces measurable and reported strain rather than a uniformly negative or positive experience.

3. Methodology

This paper adopts an integrative, narrative literature review design rather than a formal PRISMA-protocol systematic review, since the aim is conceptual synthesis across two closely related objectives rather than exhaustive enumeration of one narrow question. The review draws on peer-reviewed empirical studies, systematic reviews, and theoretical papers addressing algorithmic management, AI-driven HRM, and algorithmic governance, with particular attention to sources speaking to managerial discretion, control, and role dynamics. Recency was prioritized deliberately: the pace of AI-HR adoption accelerated sharply after 2020, and the organizational forms under discussion here did not meaningfully exist before that point.

Sources were screened for direct relevance to either objective. A source was retained only if it contributed identifiable evidence or argument to the discretion theme, the strain theme, or the conceptual scaffolding connecting the two; sources tangential to HRM were excluded regardless of citation count or venue. Screening was applied in both directions, so that every source cited below appears in the reference list and every reference-list entry is cited at least once, with no orphan citations or uncited references remaining.

The analytical approach is thematic. Sources were coded into two clusters corresponding to the two objectives, then sorted into subthemes reflecting recurrent patterns: recruitment and selection, performance management and surveillance, scheduling, sectoral variation, mediation burden, technostress, accountability ambiguity, fairness and bias, and collective responses. This mirrors approaches used within the corpus itself (Bankins et al., 2023; Owor et al., 2025). Figure 1 summarizes the thematic distribution of the sources cited across the review (Bankins et al., 2023; Owor et al., 2025).

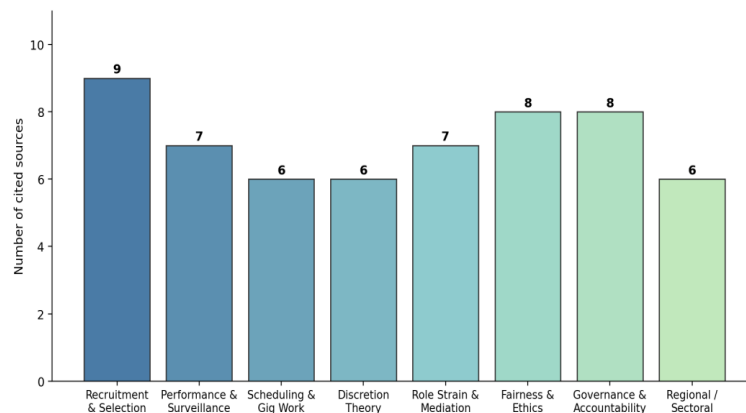


Figure 1: *Distribution of reviewed sources by thematic focus area*

Note. Counts reflect the thematic classification of the 57 sources cited in this review; some sources span more than one theme.

One limitation follows directly from the design due to the fact that this is a literature-based synthesis rather than a primary study involving interviews with practicing line managers, the paper cannot establish causal claims about the strength of the strain it identifies. What it offers instead is a conceptual model, grounded in convergent findings across independent studies, intended for empirical testing in future work.

4. Thematic Synthesis

4.1 Research Objective One: Reconfiguration of Line-Manager Discretion

4.1.1 Recruitment and Selection

Recruitment is where algorithmic substitution of managerial judgment has gone furthest. Black and van Esch (2020) flagged early how AI-enabled recruiting tools shift the manager's role from evaluator to reviewer of algorithmically ranked candidates. Li et al. (2021) interviewed recruiters and found professionals felt obligated to defer to algorithmic rankings even when their own judgment pointed elsewhere, because departing from the system's recommendation required justification the system itself did not demand.

This handoff is not neutral. Köchling and Wehner's (2020) systematic review documents how bias embedded in training data propagates through recruitment algorithms in ways individual managers are poorly positioned to detect, since scoring logic is frequently opaque even to the manager applying it. Tilmes (2022) extends this concern to disability specifically, showing recruitment algorithms can penalize candidates whose application patterns deviate from a majority baseline. Mujtaba and Mahapatra (2024) find most fairness auditing tools are technically sophisticated but poorly matched to what a line manager, lacking data science training, could plausibly interrogate before a hiring call. Hunkenschroer and Luetge (2022) frame this as an ethics gap, managers standing behind decisions whose fairness properties they cannot verify. Pessach et al. (2020) show the technical side of prescriptive recruitment analytics was mature well before the managerial implications caught up.

4.1.2 Performance Management and Surveillance-Based Control

Performance management tells a similar story through a different mechanism. Edwards et al. (2024) distinguish algorithmic HR systems perceived as managerial control from those perceived as feedback provision, finding the same system can land either way depending on how much interpretive room the manager retains. Where that room shrinks to nothing, the manager becomes a messenger for a score she did not calculate.

Surveillance intensifies this. Al Khalidi (2026) links AI-based workplace surveillance to employee calmness and citizenship behavior, with the manager's own conduct mediating the outcome. Kinowska and Sienkiewicz (2022) surveyed European organizations and found algorithmic management correlated with lower wellbeing overall, most strongly where managers had little say over how monitoring data was used against their own teams. Giermindl et al. (2021) call this the dark side of people analytics, cataloguing perils from privacy erosion to the slow erosion of a manager's standing as someone who knows her people rather than someone who merely reads a dashboard about them. Lu et al. (2024), studying platform workers, found comparable dynamics even outside standard organizational settings.

4.1.3 Scheduling and Workload Allocation

Scheduling discretion has narrowed too, arguably faster than recruitment or performance management, because scheduling lends itself readily to optimization software. Ridwan et al. (2026) identify scheduling autonomy as a key mechanism through which platform workers experience flexibility or constraint, depending on how much latitude is engineered back into the system by design. Liu et al. (2025) find algorithmic management can support team resilience by reducing objectification, but only where informal leadership, discretionary judgment exercised by someone other than the algorithm, remains active alongside the system.

Kadolkar et al. (2024) note that scheduling algorithms, more than any other application, tend to be designed with efficiency as the sole target, leaving little room for override even when a manager sees an obvious reason to intervene. Bucher et al. (2020) describe a related coping pattern: anticipatory compliance, workers adjusting behavior preemptively to satisfy a system whose exact criteria remain partly guessed at. Managers, caught between this behavior and the scheduling system itself, end up managing compliance with a black box rather than managing people directly.

4.1.4 The Enabling and Controlling Duality

None of this is uniformly bad. Noponen et al.'s (2023) grid holds both possibilities at once: the same algorithmic system can enable autonomy under one configuration and constrain it severely under another, with organizational choice often deciding which. Meijerink and Bondarouk (2021a) reach a parallel conclusion, describing algorithmic management as simultaneously restraining and enabling value creation for workers, sometimes within the same tool.

Tandon et al. (2024) interviewed managers and found genuine ambivalence rather than uniform hostility. Some described algorithmic HRM as a relief, offloading decisions they found ethically uncomfortable to make unilaterally. Others described the opposite, a loss of the discretionary space that had made the job meaningful. Cameron (2024) captures this ambivalence sharply, describing what she terms the good bad job, a role structured so that constant, confined choices manufacture a kind of consent to conditions the worker, and by extension the manager delivering them, might otherwise resist.

4.1.5 Sectoral and Regional Variation

Discretion compression is not evenly distributed globally. Adias (2025) documents digital HRM transformation in Nigerian organizations, finding impacts on talent management and wellbeing that broadly mirror patterns found elsewhere, though adoption proceeds from a different infrastructural starting point. Owor et al. (2025) reviewed Africa's preparedness for AI-driven HRM and identified gaps in the regulatory scaffolding that, in more mature markets, at least partially constrains how aggressively algorithmic systems can override managerial judgment. Said and Nahid (2026) note that most of the empirical base still concentrates in a small number of high-income economies, leaving discretion dynamics elsewhere under-examined. Ayana et al. (2024), writing on decolonizing global AI governance, argue this uneven evidence base is itself a governance problem, since frameworks built on one region's managerial norms are frequently exported wholesale to contexts where those norms do not straightforwardly apply.

Table 1 summarizes how discretion in four core domains has shifted from the traditional HRM model to the algorithmic governance model now emerging across the reviewed literature.

Table 1: Discretion Domains: Traditional HRM versus Algorithmic Governance

Decision Domain	Traditional HRM Model	Algorithmic Governance Model
Recruitment and Selection	Manager screens and interviews candidates; judgment weighs heavily in final choice	Algorithmic scoring ranks candidates; manager reviews and rarely overrides (Black & van Esch, 2020; Li et al., 2021)
Performance Evaluation	Manager observes behavior over time and interprets context before rating	Continuous system-generated metrics; manager delivers scores with limited interpretive room (Edwards et al., 2024)
Scheduling and Workload	Manager allocates shifts and tasks based on team knowledge	Optimization software assigns schedules; manager manages compliance with system output (Ridwan et al., 2026; Kadolkar et al., 2024)
Disciplinary and Reward Decisions	Manager exercises discretion grounded in situational and relational knowledge	Algorithmic flags trigger review; formal accountability remains more clearly human, though residual ethical burden persists (Hunkenschroer & Luetge, 2022)

Note. This table synthesizes patterns reported across the sources cited in section 4.1.

4.2 Research Objective Two: Role Strain and the Mediation Burden

4.2.1 Managers as Buffers and Translators

Once discretion narrows, someone still has to explain the outcome to the person it affects. Cameron (2024) describes this translation work: managers absorb employee frustration generated by a system they did not build and often cannot fully justify. Robinson et al. (2025) found managers occupying what they call a limbo position, part hierarchical authority, part passive conduit for algorithmic instruction, with the boundary shifting task by task.

Williams and Khan (2024) analyzed how HR technology vendors frame algorithmic management and found a rhetoric of manager empowerment sitting uneasily against lived experience elsewhere in the literature, a constructed antagonism between what tools are marketed to do and what managers report feeling able to do. Fenwick et al. (2024a) argue HRM's critical role in AI-driven transformation depends on this translation function being taken seriously by leadership rather than treated as solved once the software is purchased. Fenwick et al. (2024b) call for bringing humans and machines closer together in the workplace, framing the manager's mediating position as a function needing deliberate support rather than a bug to engineer away.

4.2.2 Psychological and Ethical Tension

The strain is not only structural. Dima et al. (2024) studied AI's effects across what they call the HR triad, managers, employees, and HR professionals, and found line managers reporting the least clarity about their own role going forward. Zirar et al. (2023) reviewed worker and workplace AI coexistence and identified ambiguity tolerance as an emerging theme, essentially how much uncertainty a manager can absorb before the job starts to feel untenable.

Deepa et al. (2024) examined the social and technical competencies HR managers now need and found a widening skills gap: managers are expected to interpret and defend algorithmic outputs they were never trained to evaluate. A manager asked to defend a decision she cannot audit is performing a kind of professional confidence she may not actually possess, and the cost of maintaining that performance accumulates rather than resolves.

4.2.3 Accountability Ambiguity and Algorithmic Opacity

Weiskopf and Hansen (2022) argue that algorithmic governmentality reshapes what managers are permitted to know about why a system reached a given output, and this epistemic constraint is a source of strain distinct from workload or emotional labor. Mökander et al. (2021) note that ethics-based auditing, where it exists, rarely extends far enough down the chain to give a manager more than a summary conclusion, leaving her to answer employee questions with less information than the audit itself contained.

Rodgers et al. (2022) propose an ethical decision-making approach for AI in HRM, and one central recommendation, that organizations build explainability into the manager-facing interface rather than only the system's back end, is telling precisely because it is not yet standard practice. Giermindl et al. (2021) distinguish opacity operating on two levels, technical opacity, where the algorithm's logic is genuinely inaccessible, and organizational opacity, where the logic could be shared but is withheld. Managers experience both but rarely get to tell which one they are dealing with.

4.2.4 Fairness, Bias, and the Manager's Residual Ethical Burden

Even where discretion has been formally removed, the ethical burden of a decision settles back onto the manager anyway, because employees direct grievances at a person, not a system. Tilmes's (2022) findings on disability bias mean a manager relying on an ostensibly neutral score may be unknowingly complicit in exclusion she has no visibility into and, formally, no authority to override. Mujtaba and Mahapatra (2024) note fairness auditing tools, where they exist, are typically consumed by data science or compliance teams rather than the manager actually facing the employee.

Köchling and Wehner (2020) find discrimination introduced upstream in algorithm design surfaces downstream as a managerial fairness problem, with the manager left holding responsibility for an outcome shaped by decisions made long before the position was filled. Hunkenschroer and Luetge (2022) describe the resulting position starkly: managers become the human face of decisions whose ethical architecture was set elsewhere, a role carrying real reputational and psychological cost even when the manager followed every applicable procedure correctly.

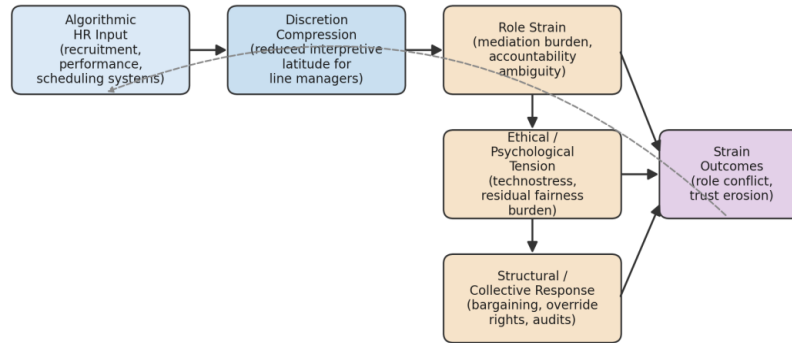
4.2.5 Collective and Structural Responses

Strain of this kind does not go unanswered indefinitely. De Stefano and Taes (2022) examine how algorithmic management intersects with collective bargaining, finding unions in several jurisdictions negotiating explicitly over algorithmic transparency and managerial override rights, treating the erosion of discretion as a bargaining issue rather than a purely technical one. Wiener et al. (2021), studying Uber drivers through a legitimacy lens, found algorithmic control retains legitimacy only so long as workers perceive some possibility of human appeal, a finding relevant to how organizations might structure manager-level override authority to preserve trust even where full discretion cannot realistically be restored.

Bowdler et al. (2025) frame algorithmic management as an emerging occupational safety and health challenge, arguing that psychosocial risk frameworks need extending explicitly to cover algorithmically mediated strain

among supervisory staff, not just frontline workers. This is, so far, more recommendation than established practice, but it points toward where structural responses are likely to develop next.

Figure 2 presents a conceptual pathway synthesizing the mechanism connecting the two objectives: algorithmic input compresses managerial discretion, which in turn generates the varieties of role strain documented across sections 4.2.1 through 4.2.5. (Authors construct)



Feedback: strain outcomes shape future organizational design choices

Figure 2: Conceptual Pathway: From algorithmic input to Line-Manager role strain

Note. Solid arrows indicate the primary strain pathway; the dashed arrow indicates a feedback loop by which strain outcomes influence subsequent organizational design choices.

5. Discussion of Findings

This section discusses the findings reported in Section 4 in the order in which they emerged, first addressing RQ1 on discretion reconfiguration, then RQ2 on role strain, before turning to the theoretical, practical, and boundary implications that follow from both sets of findings together.

5.1 Discretion Reconfiguration (RQ1)

The findings in Section 4.1 show that discretion compression is neither uniform nor accidental; it tracks how readily a decision domain lends itself to optimization. Recruitment showed the deepest compression: Black and van Esch (2020) and Li et al. (2021) both found managers shifting from evaluator to reviewer of algorithmically ranked candidates, and Köchling and Wehner (2020) found this handoff carries bias managers are poorly positioned to detect. Scheduling showed comparably deep compression through a different mechanism, Kadolkar et al. (2024) and Bucher et al. (2020) finding optimization software leaves little room for override even where a manager sees an obvious reason to intervene. Performance management showed a more contested pattern: Edwards et al. (2024) found the same system could be experienced as either control or support depending on how much interpretive room the manager retained, and Liu et al. (2025) found that where informal leadership stayed active alongside the algorithm, discretion loss did not translate into worse team outcomes. Disciplinary decisions remained the most resistant to compression, consistent with Hunkenschroer and Luetge's (2022) finding that formal accountability there stays more clearly human even as the residual ethical burden persists. Sectoral findings from Adias (2025) and Owor et al. (2025) further show this pattern is not evenly distributed globally, with infrastructural and regulatory starting points shaping how far compression has proceeded.

5.2 Role Strain and the Mediation Burden (RQ2)

The findings in Section 4.2 show that strain follows discretion compression in fairly predictable ways rather than as a diffuse byproduct. Where a manager retains genuine interpretive latitude, whether in scheduling as Liu et al. (2025) found or in performance feedback as Edwards et al. (2024) documented, strain is lower and the algorithmic system is more often experienced as support rather than replacement. Where that latitude disappears, three specific findings recur across the reviewed studies. First, a mediation-burden finding: Cameron (2024) and Robinson et al. (2025) both found managers absorbing employee frustration generated by systems they did not build and often cannot fully justify. Second, a psychological and competence finding: Dima et al. (2024) found line managers reporting the least role clarity of the HR triad, and Deepa et al. (2024) found a widening skills gap between what managers are expected to defend and what they were trained to evaluate. Third, an accountability and fairness finding: Weiskopf and Hansen (2022) and Mökander et al. (2021) found managers operate with less information than the systems they are answerable for actually contain, while Tilmes (2022) and Köchling and Wehner (2020) found the resulting fairness burden settles on the manager regardless of where the bias originated.

5.3 Theoretical Implications

This pairing of findings has a theoretical implication worth stating plainly. Much of the algorithmic management literature to date organizes itself around gig and platform work, where the worker faces the algorithm with no human intermediary at all (Wiener et al., 2021). The line-manager case differs in a way that matters. Here the human intermediary still exists, but her authority has been hollowed out from within, leaving the appearance of managerial judgment without most of its substance. Meijerink et al. (2021b) call for exactly this kind of extended attention to standard organizational settings, and the findings synthesized here suggest that call remains only partly answered.

5.4 Practical Implications

Practically, these findings mean organizations designing human-AI collaborative HR systems cannot treat the manager as a passive relay. Gong and Fan's (2024) review of AI-HRM integration argues for design choices preserving meaningful override authority at the point of delivery, not merely at the point of system design, a distinction that seems to matter enormously given the strain patterns documented above. Malik et al. (2022a) reach a similar conclusion in their extended strategic framework, recommending override rights be built into workflow architecture rather than left to informal negotiation between a manager and whatever system she happens to be using.

6. Conclusion

This paper set out to do two things. First, to trace how algorithmic management and HR algorithms are reshaping the discretionary authority line managers once exercised over recruitment, performance evaluation, scheduling, and discipline; the evidence points to compression that is real but uneven, deepest in recruitment and scheduling, more contested in performance management, and still resisted where formal accountability structures remain more clearly human. Second, to analyze the role strain that follows, mediation burden, psychological and ethical tension, accountability ambiguity, and a residual fairness burden that settles on the manager regardless of how much of the actual decision she controlled.

Konjen (2025) frames algorithmic management's future implications for autonomy, collaboration, and innovation as genuinely open questions, and the synthesis here supports that framing rather than closing it

down. Sfetcu (2024) makes a related point, that algorithmic management needs to be understood through implications for organizational development broadly, not narrowly as a technology adoption question, and the strain pathway proposed here is one attempt to answer that call with something concrete enough to test.

7. Recommendation

The following recommendations were made:

- i. It is recommended that future research should move from synthesis to direct empirical inquiry, interviews and surveys with practicing line managers across sectors, testing whether the discretion-to-strain pathway proposed here holds under measurement rather than qualitative convergence alone.
- ii. Organizations, in the meantime, would do well to treat managerial override authority not as a legacy feature to be phased out but as a design requirement, one that protects both employee trust and the wellbeing of the managers still standing, however precariously, between the algorithm and the person it governs.

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