



From Algorithmic HRM to Employee Voice: Theorising Autonomy, Justice, Inclusion and Trust in AI-enabled Workplace Governance

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Abstract:

Artificial intelligence is changing human resource management not only by accelerating decisions but also by altering the conditions under which employees are assessed, compared and heard. Algorithmic systems now inform recruitment screening, performance appraisal, work scheduling, reward allocation, promotion recommendations and disciplinary decisions. Although these systems are frequently introduced as instruments of consistency and evidence-based management, their use in HRM also raises difficult questions about autonomy, fairness, inclusion, trust and employee voice. This conceptual paper develops a theory-based model explaining how algorithmic control in HRM may shape employee voice through employees' experiences of task autonomy, organisational justice, workplace inclusion and trust in AI-enabled HR decisions. Drawing on algorithmic control literature, job characteristics theory, self-determination theory, organisational justice theory and social exchange theory, the paper argues that algorithmic HRM becomes consequential because it reorganises discretion, visibility and accountability in everyday work. The model proposes that employees are more likely to respond constructively when algorithmic HRM preserves meaningful discretion, provides fair and explainable procedures, recognises diverse work realities and sustains trust. Conversely, opaque or exclusionary systems may encourage silence, formal complaint or collective action. The paper contributes to algorithmic HRM scholarship by theorising employee voice as a central condition of legitimate AI-enabled workplace governance.

Keywords: Algorithmic HRM; algorithmic control; employee voice; task autonomy; organisational justice; workplace inclusion; trust in AI; workplace governance

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1. INTRODUCTION

Human resource management has always involved judgement. Managers and HR professionals decide who should be hired, how performance should be assessed, which employees deserve development opportunities, how rewards should be distributed and when disciplinary intervention is justified. These decisions are never purely administrative. They shape employees' income, status, confidence and future position in the organisation. The arrival of artificial intelligence and algorithmic systems has not removed this judgement; rather, it has changed the way judgement is organised, supported and justified.

AI-enabled HRM now appears in a growing range of organisational practices. Applicant-tracking systems rank candidates, monitoring tools record employee activity, scheduling systems allocate shifts, analytics platforms identify performance patterns, and decision-support systems inform promotion, reward and disciplinary decisions. Such tools are often adopted because they promise efficiency, consistency and data-informed decision-making. In large organisations, where HR professionals face extensive information and time pressure, these promises are attractive. Algorithmic systems can process data at a scale that human decision-makers cannot easily match. They may also expose patterns that would otherwise remain hidden (Budhwar et al., 2023; Marler & Boudreau, 2017; Tambe et al., 2019).

Yet the managerial appeal of algorithmic HRM should not obscure its social consequences. A system that produces an appraisal score, a risk alert or a promotion recommendation does more than assist decision-making. It shapes what the organisation treats as relevant evidence. It may privilege some indicators over others, make certain forms of work visible and leave other contributions outside the frame. It may also influence how employees behave, because employees quickly learn which behaviours are measured, rewarded or penalised. In this sense, algorithmic HRM is not simply a technical extension of digital HRM. It is part of the contemporary governance of work.

The concept of governance is important here. HRM is one of the main channels through which organisational authority is exercised. Decisions about recruitment, appraisal, rewards, promotion and discipline communicate what the organisation values and how it expects employees to conduct themselves. When algorithmic systems enter these processes, authority becomes partly mediated by data, models, dashboards and automated recommendations. Human actors remain involved, but their judgement may be framed by system outputs that appear objective, precise or administratively defensible. As Berente et al. (2021) and Raisch and Krakowski (2021) suggest in wider debates on artificial intelligence and management, AI rarely produces a simple substitution of humans by machines. More often, it creates hybrid arrangements in which human and algorithmic contributions become intertwined.

This hybrid character makes algorithmic HRM difficult to evaluate. On the one hand, algorithmic systems can support HR decisions by reducing information overload, increasing consistency and helping organisations detect patterns across employee data. On the other hand, they may reproduce bias, intensify surveillance, narrow discretion or obscure accountability (Kellogg et al., 2020; Leicht-Deobald et al., 2019; Vassilopoulou et al., 2024). The same system can be experienced differently by different employees. A performance dashboard may be useful feedback for one employee and a source of pressure for another. A standardised appraisal model may reduce arbitrary managerial bias in one context and misrecognise contextual effort in another. The question, therefore, is not whether algorithmic HRM is inherently beneficial or harmful. The more important question is how employees experience and respond to algorithmically mediated authority.

Employee voice provides a useful lens for this question. Voice refers to the expression of suggestions, concerns, disagreement or dissatisfaction about work-related matters (Morrison, 2014; Van Dyne & LePine, 1998). In a narrow sense, voice may involve constructive speaking up intended to improve organisational functioning. In a broader employment relations sense, it also includes formal grievance procedures, complaint mechanisms,





collective representation and coordinated employee action (Dundon et al., 2004; Wilkinson et al., 2004). This broader understanding is necessary in algorithmic HRM because employee responses are unlikely to take only one form. Employees may raise concerns informally when they trust the organisation. They may use formal routes when they need procedural protection. They may act collectively when algorithmic systems appear to create shared disadvantage. They may also remain silent when the system seems impossible to question.

The link between algorithmic HRM and employee voice remains insufficiently theorised. Existing scholarship has developed important insights into algorithmic management, digital HRM and the ethics of AI-enabled decision-making. Studies of platform work show how algorithms can direct, evaluate and discipline workers through ratings, task allocation, automated sanctions and limited appeal routes (Curchod et al., 2020; Duggan et al., 2023; Rosenblat & Stark, 2016). HRM scholars have examined how AI and analytics change HR functions, managerial roles and employment relations (Charlwood & Guenole, 2022; Meijerink et al., 2021; Parent-Rocheleau & Parker, 2022). Ethical work has highlighted opacity, bias, accountability and the limits of algorithmic neutrality (Barocas & Selbst, 2016; Mittelstadt et al., 2016). What is still needed is a clearer explanation of how algorithmic HRM affects employees' willingness and capacity to speak, challenge, complain or participate in shaping the systems that govern them.

This paper addresses that gap by developing a conceptual model that links algorithmic control in HRM with employee voice through four theoretical domains: task autonomy, organisational justice, workplace inclusion and trust in AI-enabled HR decisions. Task autonomy is included because algorithmic control can reshape employees' discretion over work methods, pacing, scheduling and decision-making. This argument draws on job characteristics theory and self-determination theory, both of which treat autonomy as central to meaningful and self-regulated work (Deci & Ryan, 2000; Gagné & Deci, 2005; Hackman & Oldham, 1976; Morgeson & Humphrey, 2006). Organisational justice is included because employees judge HR decisions not only by their outcomes but also by the fairness, transparency and correctability of the procedures through which those outcomes are produced (Colquitt, 2001; Cropanzano et al., 2007; Greenberg, 1990). Workplace inclusion is included because algorithmic systems may recognise some forms of contribution and difference more readily than others (Nishii, 2013; Shore et al., 2011). Trust is included because employee voice depends partly on whether employees believe that AI-enabled HR decisions are competent, fair, explainable and accountable (Glikson & Woolley, 2020; Mayer et al., 1995).

The paper makes three contributions. First, it reframes algorithmic HRM as AI-enabled workplace governance. This moves the discussion beyond adoption, efficiency and technical functionality, and places attention on discretion, legitimacy and participation. Second, it integrates job design, justice, inclusion and trust perspectives to explain why algorithmic control may affect employee agency. Rather than treating these constructs as separate outcomes, the paper theorises them as connected interpretive conditions through which employees evaluate algorithmically mediated HR decisions. Third, it extends employee voice theory into AI-enabled HRM contexts by explaining how trust may shape whether employees remain silent, speak informally, use formal channels or participate in collective forms of action.

The article proceeds as follows. The next section develops the idea of algorithmic HRM as workplace governance. The following section sets out the theoretical foundations of the model. Subsequent sections examine task autonomy, fairness perceptions, workplace inclusion and trust before turning to employee voice. The paper then presents formal propositions and discusses theoretical, practical and future research implications.

2. Algorithmic HRM as AI-enabled Workplace Governance

Algorithmic HRM refers to the use of algorithmic, artificial intelligence or advanced analytics systems to support, shape or automate decisions concerning employees (Cheng & Hackett, 2021; Meijerink et al., 2021). The phrase covers a wide range of practices. Some systems screen applicants or recommend candidates for interview. Others track employee activity, allocate shifts, compare performance, estimate attrition risk, identify high-potential





employees, suggest rewards or flag conduct concerns. These applications differ in sophistication. Some involve relatively simple scoring rules, while others rely on machine learning or predictive analytics. What they share is a shift in the role of employee data. Data are no longer used only for record-keeping. They become part of how employees are evaluated, governed and made visible to the organisation.

This distinguishes algorithmic HRM from ordinary HR digitalisation. A digital payroll system may improve administrative efficiency without changing how employee contribution is judged. A self-service leave portal may speed up routine transactions without producing behavioural control. Algorithmic HRM is different because it enters the interpretive space of people management. It can classify employees, recommend action, set priorities for managerial attention and define what counts as evidence. In this respect, algorithmic HRM sits close to the field of HR analytics, but it carries a stronger governance implication. HR analytics often refers to the systematic use of workforce data for decision support (Marler & Boudreau, 2017; Tursunbayeva et al., 2018). Algorithmic HRM adds the possibility that data-driven systems will actively organise, rank or recommend decisions concerning employees.

The appeal of such systems is understandable. Human decision-making in HR can be inconsistent, biased and constrained by limited information. Managers may rely on memory, subjective impressions or informal preferences. HR professionals may struggle to process large quantities of data across departments, locations and employment categories. Algorithmic systems promise a more systematic basis for judgement. They can process information quickly, apply criteria consistently and detect patterns that may escape unaided human attention. These possibilities explain why organisations often present algorithmic HRM as an improvement over informal managerial discretion.

However, the claim of neutrality requires careful examination. Algorithms do not emerge outside organisational life. They are designed, purchased, configured and interpreted within particular institutional settings. Data selection, model design, measurement priorities and implementation choices all reflect assumptions about what matters and whose interests count (Mittelstadt et al., 2016; Vassilopoulou et al., 2024). Historical workforce data may carry traces of prior inequality. Performance indicators may capture only what is easy to quantify. Vendor systems may contain categories that do not fit local work realities. A technically consistent system may therefore reproduce unfairness with greater speed and legitimacy than an inconsistent human decision-maker.

Algorithmic control is a useful way to understand this problem. Kellogg et al. (2020) describe algorithms at work as a new terrain of control because they can direct, evaluate and discipline employees through systems that are not always transparent. In platform work, this control is often visible. Drivers, delivery workers and online freelancers may be allocated tasks, evaluated through ratings, sanctioned through automated mechanisms and given limited channels to appeal decisions (Curchod et al., 2020; Duggan et al., 2023; Rosenblat & Stark, 2016). Conventional organisations may not operate in exactly the same way, but the underlying logic increasingly travels into mainstream HRM. Performance dashboards, monitoring systems, algorithmic scheduling tools and AI-enabled appraisal systems can all shape employee behaviour without issuing explicit managerial commands.

The distinctive feature of algorithmic control in HRM is that it operates through decisions with direct consequences for employees' organisational lives. Recruitment affects entry. Appraisal affects recognition and career prospects. Rewards affect material outcomes. Scheduling affects time and work-life boundaries. Promotion systems affect status and mobility. Disciplinary tools affect security and dignity. When algorithmic systems

influence these areas, they become part of organisational authority. They do not merely produce information; they help structure the conditions under which employees are judged.

This does not mean that algorithmic systems replace managers. In most organisations, the more plausible pattern is hybrid decision-making. Managers remain formally responsible, but their judgement is shaped by system outputs. A score may make one employee appear more productive than another. A risk flag may draw managerial attention to one worker and not another. A recommendation may become difficult to ignore because it appears





evidence-based. The human actor is still present, but the field of action has changed. Algorithmic HRM therefore works not only through automation but also through framing. It frames what is visible, credible and defensible.

Employees are not unaware of this. Even when they do not know the details of a system, they may adjust their conduct around what they believe is being measured. If response time is monitored, speed may become a priority. If customer ratings influence appraisal, employees may manage impressions differently. If digital availability is treated as commitment, workers may remain continuously reachable. Algorithmic control can therefore operate through anticipation. Employees regulate themselves in relation to expected system evaluation.

For this reason, the paper conceptualises algorithmic HRM as AI-enabled workplace governance. Workplace governance refers to the ways organisations regulate behaviour, allocate opportunities, define accountability and organise participation. Algorithmic HRM contributes to governance by shaping what is measured, how decisions are justified, whose work is recognised and how employees may challenge outcomes. This perspective is broader than a technology-adoption view. It asks not only whether algorithmic HRM is efficient, but also whether it preserves autonomy, sustains justice, recognises difference, supports trust and enables voice.

3. Theoretical Foundations of the Conceptual Model

The conceptual model developed in this paper draws on five bodies of scholarship: algorithmic control literature, job characteristics theory, self-determination theory, organisational justice theory and social exchange theory. Each contributes a different part of the explanation. Algorithmic control literature clarifies how data-driven systems reorganise authority and visibility. Job characteristics theory and self-determination theory explain why autonomy matters for meaningful work and employee agency. Organisational justice theory explains how employees evaluate the legitimacy of HR outcomes and procedures. Inclusion theory adds attention to recognition, difference and participation. Social exchange theory then helps explain why these experiences influence trust and voice.

Algorithmic control literature provides the starting point. Traditional organisational control has relied on supervisors, bureaucratic rules, targets, professional norms and market pressures. Algorithmic control adds a further layer by embedding direction and evaluation into digital systems (Kellogg et al., 2020). A worker may not be directly ordered to behave in a certain way, but dashboards, rankings, ratings and automated alerts can make some behaviours safer, more visible or more rewarding than others. The system becomes a silent participant in the employment relationship. This is particularly important in HRM because employees may not know whether a decision is primarily managerial, algorithmic or some combination of both.

Job characteristics theory helps explain why this matters for work experience. Hackman and Oldham (1976) identified autonomy as one of the core characteristics of motivating work. Morgeson and Humphrey (2006) later elaborated autonomy as involving discretion over scheduling, decision-making and work methods. Algorithmic HRM can affect each of these dimensions. Automated scheduling may reduce control over time. Monitoring systems may influence pace. Performance dashboards may constrain how employees choose work methods. The issue is not only whether employees technically retain freedom. It is whether the structure of evaluation makes such freedom meaningful.

Self-determination theory sharpens this point by treating autonomy as a basic psychological need (Deci & Ryan, 2000; Gagné & Deci, 2005). Employees need to experience their actions as self-endorsed rather than merely externally compelled. Algorithmic HRM may threaten this experience when employees feel constantly monitored, scored or nudged by systems they do not understand. Yet the relationship is not automatically negative. A system that gives useful feedback, reduces uncertainty or supports employee choice may strengthen autonomy. What matters is whether technology enlarges informed discretion or narrows work into compliance with measurable indicators.





Organisational justice theory is the second major foundation. HRM decisions are closely tied to fairness because they distribute rewards, recognition, opportunities and sanctions. Colquitt (2001) distinguishes distributive, procedural, interpersonal and informational justice. In algorithmic HRM, distributive justice concerns whether outcomes influenced by systems are seen as fair. Procedural justice concerns whether the decision process is consistent, accurate, correctable and open to voice. Informational justice concerns whether employees receive adequate explanation about how decisions are made (Greenberg, 1990). These distinctions are crucial because a technically consistent decision may still be experienced as unfair if the procedure is opaque or uncorrectable.

Workplace inclusion extends the argument beyond formal fairness. Inclusion concerns whether employees feel respected, valued and able to participate fully while retaining meaningful aspects of difference (Nishii, 2013; Shore et al., 2011). Algorithmic HRM may support inclusion when it helps identify inequity or reduces arbitrary managerial judgement. It may also weaken inclusion when it misrecognises employees whose work patterns, communication styles, caregiving responsibilities, disability-related adjustments or occupational contexts do not fit standardised metrics. Inclusion therefore asks a question that fairness alone may not fully capture: who is made legible by the system, and who is reduced or overlooked?

Social exchange theory provides the final link. Employees respond to organisational treatment through reciprocal attitudes and behaviours (Blau, 1964; Cropanzano & Mitchell, 2005). When employees experience HR systems as fair, respectful and accountable, they are more likely to develop trust and engage constructively. When they experience decisions as imposed, opaque or exclusionary, they may withdraw, remain silent or seek formal and collective remedies. Trust becomes the interpretive bridge between employees' experience of algorithmic HRM and their behavioural response.

The model therefore proposes a theoretical chain. Algorithmic control in HRM first reshapes employees' experience of work and decision-making. Those experiences influence perceptions of autonomy, justice and inclusion. These perceptions then affect trust in AI-enabled HR decisions. Trust, in turn, shapes whether employees speak informally, use formal channels, participate collectively or remain silent. The model does not treat employees as passive recipients of technology. It positions them as organisational actors whose agency depends partly on whether algorithmic governance is intelligible, fair and open to challenge.

4. Algorithmic Control, Job Quality and Task Autonomy

Task autonomy is one of the most direct routes through which algorithmic HRM enters employees' experience of job quality. Autonomy refers to the degree of discretion employees have over work methods, work scheduling and task-related decisions (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006). It allows employees to adapt to local demands, use professional judgement and take responsibility for outcomes. In many jobs, good work depends precisely on this discretion. Teachers, nurses, customer-service staff, software professionals, managers and field employees all rely on contextual judgement that cannot be fully captured by standardised indicators.

Algorithmic HRM can narrow autonomy by expanding visibility and measurement. Monitoring systems record activity. Dashboards translate behaviour into scores. Scheduling tools allocate time. Performance analytics compare employees against targets or peers. These practices may not remove discretion formally, but they can change its practical meaning. Employees may ask themselves not what the work requires, but what the system will recognise. They may choose behaviours that improve measurable performance even when other behaviours would be more valuable in context. The result is a subtle shift from professional judgement to metric-oriented self-management.

This mechanism can be described as anticipatory compliance. Employees do not need to be instructed directly if they know that particular indicators are tracked and evaluated. They may regulate pace, communication, availability or task focus in line with system expectations. In some cases, this may improve clarity. In others, it may compress the range of acceptable behaviour. The problem is especially acute when complex work is reduced to





narrow indicators. A customer-service employee may be judged by call duration, although good service sometimes requires patience. A manager may be assessed through team output, although part of the role involves mentoring, conflict resolution or emotional support. An academic or professional employee may be evaluated through visible outputs while less visible forms of contribution remain under-recognised.

The relationship is not one-sided. Algorithmic systems can also support autonomy when they provide employees with timely information, reduce uncertainty or allow more informed choices. A scheduling system that incorporates employee preferences may improve control over time. A performance system used for developmental feedback may help employees identify areas for growth. A workload analytics tool may reveal overburdening and support fairer task distribution. Parker and Grote (2022) argue that digital technologies can either enrich or degrade work depending on design and implementation. This distinction is central to algorithmic HRM. The same category of tool may be enabling or controlling depending on whether employees can understand, influence and contest its use.

Autonomy also affects how employees interpret algorithmic HR decisions. If a system preserves room for contextual judgement, employees may see it as supportive. If it narrows discretion and rewards only measurable compliance, they may view it as a mechanism of control. Trust in AI-enabled HR decisions is therefore partly rooted in work design. Employees are unlikely to trust decisions that appear detached from the realities of their work. Even technically accurate systems may lose legitimacy if they fail to respect the judgement needed for good performance.

Proposition 1: Algorithmic control in HRM is likely to reduce employees' perceived task autonomy when algorithmic systems intensify monitoring, standardisation and performance visibility.

Proposition 2: Perceived task autonomy is likely to strengthen employees' trust in AI-enabled HR decisions when algorithmic systems preserve discretion, contextual judgement and meaningful human involvement.

5. Algorithmic HRM and Fairness Perceptions

Fairness is a central concern in algorithmic HRM because HR decisions allocate valued organisational outcomes. Employees care about pay, appraisal ratings, promotion opportunities, development access, scheduling and discipline not only because these decisions have material effects, but also because they communicate worth. A fair decision tells employees that their contribution has been recognised and that they have been treated as legitimate organisational members. An unfair decision does the opposite.

Organisational justice theory helps explain how employees make these judgements. Distributive justice concerns whether outcomes are fair. Procedural justice concerns whether the process through which outcomes are produced is fair. Informational justice concerns whether explanations are adequate, truthful and understandable (Colquitt, 2001; Greenberg, 1990). Algorithmic HRM complicates all three dimensions because employees may have to evaluate decisions whose underlying logic is partly hidden within data, models and system design.

Distributive justice is affected when algorithmic systems influence outcomes such as appraisal scores, performance rankings, incentives, promotion recommendations or disciplinary flags. Employees may view such outcomes as fair when the system uses relevant and accurate information. A well-designed system might reduce

favouritism, apply criteria consistently and detect overlooked patterns of contribution. However, the same system may damage distributive justice if its data are incomplete, biased or insensitive to context. A productivity metric may measure speed but not quality. A promotion model may reflect historical patterns that already favoured certain groups. A disciplinary alert may overstate risk because it lacks contextual explanation. In such cases, algorithmic precision can give partial evidence an undeserved authority.

Procedural justice is equally important. Leventhal's (1980) criteria of consistency, bias suppression, accuracy, correctability, representativeness and ethicality remain highly relevant to AI-enabled HR decisions. Employees





may ask whether the same rules are applied across groups, whether the data are accurate, whether the system can be corrected and whether their perspective can be included. Algorithmic opacity makes these questions harder to answer. A decision may be formally consistent but practically unchallengeable. It may be data-based but not representative. It may include human review but only as a symbolic approval of an automated output.

Informational justice adds a communicative dimension. Employees need explanations that are meaningful to them, not only to technical specialists. A statement that an algorithm was used is not sufficient. Nor is a complex technical description useful if it cannot be understood by the person affected by the decision. Explainability in HRM is therefore relational. It involves telling employees what data were considered, how those data mattered, what role human judgement played and how errors can be corrected. Without such explanation, algorithmic HRM can feel like a closed authority system.

Recent work on algorithmic reductionism makes this concern sharper. Newman et al. (2020) argue that attempts to remove bias through algorithmic decision-making may still violate procedural justice when people feel reduced to narrow data points. This is directly relevant to HRM. Employees may object not only to incorrect outcomes but also to the feeling that their work, identity or context has been flattened into a score. Fairness, then, is not merely a matter of removing human bias. It requires procedures that employees can recognise as legitimate.

Fairness perceptions also shape trust. Social exchange theory suggests that fair treatment communicates respect and supports reciprocal engagement (Blau, 1964; Cropanzano & Mitchell, 2005). In algorithmic HRM, fair procedures and adequate explanations may encourage employees to trust AI-enabled decisions. Opaque, uncorrectable or context-insensitive systems may instead produce suspicion. Employees may comply with such systems because they lack power, but compliance should not be mistaken for trust.

The implications for voice are significant. If employees believe an outcome is unfair but the process is open and correctable, they may speak up constructively. If they believe both outcome and process are unfair, voice may become riskier and more adversarial. Some employees may remain silent. Others may use grievance mechanisms or collective channels. Fairness is therefore not only an evaluative judgement; it influences the perceived safety and usefulness of speaking.

Proposition 3: Algorithmic control in HRM is likely to weaken distributive justice perceptions when algorithmically influenced outcomes are based on incomplete, inaccurate or context-insensitive data.

Proposition 4: Algorithmic control in HRM is likely to weaken procedural justice perceptions when employees perceive AI-enabled HR decisions as opaque, difficult to challenge or insufficiently subject to human review.

Proposition 5: Informational justice is likely to strengthen trust in AI-enabled HR decisions when employees receive clear, relevant and understandable explanations of how algorithmic inputs are used.

Proposition 6: Perceived procedural justice is likely to mediate the relationship between algorithmic control in HRM and trust in AI-enabled HR decisions.

6. Workplace Inclusion in Algorithmic HRM

Inclusion is often discussed after fairness, but in algorithmic HRM it deserves independent attention. Fairness asks whether employees are treated properly according to relevant standards. Inclusion asks whether employees feel recognised, valued and able to participate while retaining meaningful aspects of difference (Nishii, 2013; Shore et al., 2011). A workplace can be formally fair and still feel exclusionary if its systems recognise only a narrow version of contribution.

Algorithmic HRM may support inclusion when used carefully. HR analytics can reveal unequal promotion patterns, inconsistent appraisal outcomes or biased access to developmental opportunities. AI-enabled systems may





reduce some arbitrary managerial preferences and make decisions more consistent. Ajunwa (2020), however, cautions that automation presented as anti-bias intervention can produce its own paradoxes. A system may claim to remove human bias while embedding earlier inequalities into data, categories or predictive models. Inclusion therefore depends not simply on whether a system is automated, but on how it defines, measures and values employee difference.

Historical data are rarely neutral. They carry the imprint of earlier decisions about who was hired, promoted, rewarded or overlooked. If those patterns are used to train HR systems, past exclusion may be translated into future recommendation. A promotion algorithm may learn from career paths that were easier for some groups to follow. A performance model may overvalue visible individual output and undervalue collaboration or relational labour. A monitoring system may treat continuous availability as commitment, thereby disadvantaging employees with caregiving responsibilities or health-related needs.

Context is another inclusion problem. Employees do not perform under identical conditions. Job roles, resources, client expectations, team support, digital familiarity and personal circumstances vary substantially. A standardised metric may therefore carry different meanings across groups. Response time may indicate efficiency in one role and superficiality in another. High digital visibility may reflect commitment for some employees and role design for others. The danger is that algorithmic systems may treat difference as noise rather than as information necessary for fair interpretation.

The distinction between equality and inclusion is helpful. Equality often implies the same rule for everyone. Inclusion requires sensitivity to difference and participation in shaping organisational practices (Ferdman, 2014; Nishii, 2013). Algorithmic HRM may satisfy a narrow equality test by applying uniform criteria, yet still fail inclusion if those criteria misrecognise diverse work realities. Inclusive algorithmic governance would require employees to have some voice in how categories are defined, how data are interpreted and how exceptions or contextual factors are considered.

Inclusion is closely linked with trust. Employees are more likely to trust AI-enabled HR decisions when they believe that the organisation has considered the complexity of their work and circumstances. Trust weakens when employees feel reduced to narrow indicators or misrecognised by systems that claim neutrality. This is not only a problem of technical bias. It is also a problem of organisational respect. Employees need to believe that their difference, dignity and participation matter.

Inclusion also shapes employee voice. Employees who feel respected are more likely to raise concerns constructively because they expect their views to be taken seriously. Employees who feel excluded may decide that speaking up is pointless. In other cases, exclusion may push them towards formal complaint or collective action, particularly when the problem appears systemic. Inclusion therefore influences both trust in algorithmic HRM and the form of response employees consider available.

Proposition 7: Algorithmic control in HRM is likely to weaken workplace inclusion when AI-enabled systems misrecognise diverse work contexts, employee circumstances or forms of contribution that are difficult to quantify.

Proposition 8: Perceived workplace inclusion is likely to strengthen trust in AI-enabled HR decisions by signalling that algorithmic HRM recognises employee difference, dignity and participation.

7. Trust in AI-enabled HR Decisions

Trust occupies a central position in the proposed model because it links employee experience with employee response. Mayer et al. (1995) define trust as a willingness to accept vulnerability based on positive expectations about another party's ability, benevolence and integrity. In HRM, employees are often vulnerable. They depend





on decisions about appraisal, promotion, reward, scheduling and discipline that they cannot fully control. When such decisions are shaped by algorithmic systems, the object of trust becomes more complex.

Employees may trust a manager but distrust the algorithmic tool used by that manager. They may trust the technical competence of a system but distrust the organisational purpose behind it. They may accept that a model is accurate in general while doubting whether it understands their work. Trust in AI-enabled HR decisions therefore cannot be reduced to trust in technology. It involves the system, the human decision-maker and the organisational governance surrounding both.

Glikson and Woolley (2020) identify capability, transparency, tangibility and task type as important influences on trust in AI. In HRM, these factors are filtered through employment relations. Employees ask whether the system is competent, but they also ask whether it is fair, accountable and used for legitimate purposes. A highly capable monitoring tool may still be distrusted if employees experience it as surveillance. A predictive appraisal system may be technically sophisticated and still illegitimate if employees cannot understand or correct its outputs.

Competence-based trust and integrity-based trust are both necessary. Competence-based trust concerns whether the system processes relevant information accurately. Integrity-based trust concerns whether the organisation uses the system responsibly. Neither is sufficient alone. A competent system may be used in a punitive way. An ethical organisation may adopt a flawed system. Trust in AI-enabled HR decisions depends on the combined legitimacy of data, design, interpretation and oversight.

Opacity remains one of the main barriers. Employees do not need to understand every mathematical detail of a model, but they do need enough explanation to judge relevance and accountability. They need to know what data were used, whether errors can be corrected and whether a human actor can meaningfully review the decision. Research on trust in automation suggests that both over-reliance and under-reliance can be problematic (Hoff & Bashir, 2015; Lee & See, 2004). In algorithmic HRM, managers may over-rely on system outputs because they appear objective. Employees may under-trust those outputs because they appear closed, impersonal or detached from lived work.

Human oversight is often proposed as a solution, but it must be substantive. A manager who merely endorses an algorithmic recommendation does not provide meaningful accountability. Human oversight requires time, authority and competence to question the system. It also requires that employees know how to request review. Otherwise, the human presence becomes symbolic, and trust may decline further. Jarrahi (2018) and Raisch and Krakowski (2021) both emphasise that human-AI collaboration depends on the quality of the relationship between human judgement and machine output. In HRM, that relationship must be visible enough for employees to trust it.

Trust then shapes voice. When employees trust AI-enabled HR decisions, they may speak informally because they expect the organisation to listen and respond. When trust is uncertain, employees may prefer formal channels because these provide documentation and protection. When trust is low, employees may remain silent, withdraw or participate in collective action. Trust therefore does not merely determine acceptance of algorithmic HRM. It shapes the form of agency employees consider possible.

Social exchange theory helps explain why. Fair and accountable treatment encourages constructive reciprocity (Blau, 1964; Cropanzano & Mitchell, 2005). Employees who believe that algorithmic HRM is used responsibly may be more willing to raise concerns in ways that help the organisation improve. Employees who experience algorithmic HRM as opaque, exclusionary or controlling may see little reason to offer constructive participation. Voice may then become defensive, formal or collective rather than informal and developmental.

Proposition 9: Employees' trust in AI-enabled HR decisions is likely to be strengthened when algorithmic HRM preserves autonomy, supports procedural fairness and recognises workplace inclusion.





Proposition 10: Trust in AI-enabled HR decisions is likely to mediate the relationship between employees' perceptions of autonomy, justice and inclusion and their use of employee voice.

8. Employee Voice under AI-enabled Workplace Governance

Employee voice is the final outcome in the proposed model because it shows whether employees can respond to algorithmic HRM as active organisational members. Voice is often defined as discretionary expression of ideas, concerns or suggestions intended to improve the organisation (Van Dyne & LePine, 1998). Morrison (2014) expands this discussion by connecting voice with silence, risk and employee judgement. Employment relations scholars add another dimension by emphasising complaint, dissatisfaction, formal representation and collective action (Dundon et al., 2004; Wilkinson et al., 2004). Algorithmic HRM requires this wider view because employees may not always respond through polite suggestion. Their response may depend on whether they trust the system and whether credible routes for challenge exist.

Algorithmic HRM changes the conditions of voice by making responsibility harder to locate. In conventional HRM, an employee can usually identify the manager, HR officer or committee responsible for a decision. In AI-enabled HRM, a decision may emerge from data inputs, vendor design, model assumptions, HR policy and managerial interpretation. An employee who receives a low algorithmically influenced appraisal score may not know whether to question the data, the model, the manager or the policy that authorised the system. This diffusion of responsibility can make voice more difficult even when employees are willing to speak.

Informal voice is most likely when employees believe that the organisation will listen. In algorithmic HRM, informal voice may involve telling a supervisor that a metric is inaccurate, asking HR to review a recommendation, or explaining that a system has misunderstood the work context. Such voice depends on trust. Employees need to believe that speaking up will not be dismissed as resistance to technology. They also need to believe that the person receiving the concern has enough authority to act.

Formal voice becomes more attractive when trust is weaker or when the issue affects important outcomes. Appeals, grievance mechanisms, ethics hotlines, complaint systems and formal feedback platforms can provide structure and documentation. They may also protect employees from the informality of managerial discretion. However, formal channels must be designed for algorithmic HRM. A general complaint form may not help employees challenge data accuracy, model logic or automated recommendations. Voice mechanisms need to specify what employees can contest, what evidence they can provide and who is responsible for review.

Collective voice becomes relevant when employees experience algorithmic HRM as a shared issue. Monitoring systems, productivity metrics and appraisal algorithms are rarely isolated to one person. They often apply across teams, departments or occupational groups. When employees perceive that an algorithmic system creates common disadvantage, collective action may become a reasonable response. This may occur through unions, employee forums, coordinated complaints or public contestation. Collective voice should not be treated only as resistance. It can reveal systemic problems that individual complaints cannot identify.

Silence must be included in the model because it is a likely response to opaque algorithmic authority. Employees may remain silent when they believe that algorithmic outputs cannot be changed, that managers will defer to the system or that speaking up may expose them to further scrutiny. Silence may also arise when employees lack the technical language to challenge a decision. A manager's judgement can be disputed as judgement; an algorithmic score may appear more difficult to contest because it carries the aura of data.

The form of voice therefore depends on trust, perceived safety and the availability of meaningful channels. High trust may support informal voice. Moderate trust may encourage formal channels. Low trust may produce silence, withdrawal or collective action. The implication is that responsible algorithmic HRM cannot treat voice as an afterthought. If employees cannot question the systems that evaluate them, AI-enabled HRM lacks democratic legitimacy within the workplace.





Proposition 11: Trust in AI-enabled HR decisions is likely to increase employees' use of constructive informal voice when employees believe that algorithmically influenced decisions are fair, intelligible and correctable.

Proposition 12: Low trust in AI-enabled HR decisions is likely to increase employee silence when employees believe that algorithmic outputs cannot be meaningfully questioned or changed.

Proposition 13: Employees are more likely to use formal or collective voice when algorithmic HRM is perceived as opaque, unfair or harmful across groups rather than as an isolated individual concern.

9. Discussion and Theoretical Contributions

This paper has developed a conceptual model linking algorithmic control in HRM with employee voice through autonomy, justice, inclusion and trust. Its central argument is that algorithmic HRM should be understood as workplace governance rather than as a neutral technical support system. Once algorithmic tools influence monitoring, appraisal, scheduling, rewards, promotion or discipline, they become part of the way organisational authority is exercised.

The first contribution lies in reframing algorithmic HRM around employee agency. Much discussion of AI in HRM begins with efficiency, prediction and consistency. These themes are important, but they do not fully address employees' lived experience of algorithmic authority. By placing employee voice at the centre, this paper asks whether employees can understand, question and influence the systems that shape their organisational lives. This moves algorithmic HRM scholarship beyond adoption and functionality towards legitimacy and participation.

The second contribution is theoretical integration. Job characteristics theory and self-determination theory explain why autonomy matters when algorithmic systems intensify visibility and standardisation. Organisational justice theory explains how employees judge the fairness of algorithmically influenced outcomes, procedures and explanations. Inclusion theory highlights the risk that standardised systems may misrecognise difference. Social exchange theory clarifies why fair and inclusive treatment supports trust and constructive participation. The contribution is not simply the addition of several variables. It is the development of a theoretical chain linking control, interpretation and voice.

The third contribution concerns voice theory. Voice scholarship has long examined why employees speak up or remain silent. Algorithmic HRM introduces a new problem: employees may not know where responsibility lies. They may be affected by decisions produced through a chain of data, model design, vendor architecture, HR policy and managerial interpretation. This complicates the usual assumptions about speaking to a manager or using an organisational channel. The model therefore shows how trust in AI-enabled HR decisions can shape whether voice is informal, formal, collective or absent.

The paper also clarifies why trust should not be treated as a simple acceptance variable. Trust in algorithmic HRM is not passive approval of technology. It is an evaluative judgement about competence, fairness, accountability and recognition. Employees may comply without trusting. They may accept an outcome while doubting the process. They may trust the organisation but not the system. These distinctions are important for future research because they show why algorithmic HRM cannot be evaluated only through adoption rates or employee attitudes towards technology in general.

10. Practical Implications

For organisations, the main implication is that responsible algorithmic HRM requires governance, not only technical procurement. HR leaders should ask whether AI-enabled systems preserve meaningful autonomy, provide fair procedures, recognise diverse employee circumstances and support trust. Technical accuracy matters, but it is not enough. A system that is accurate yet opaque, unchallengeable or insensitive to context may still damage legitimacy.





Organisations should therefore provide employees with clear explanations of how algorithmic inputs are used. These explanations should not be limited to technical documentation. Employees need practical information: what data matter, how decisions are reviewed, what role managers play and how errors can be corrected. Informational justice is a central part of responsible implementation.

Human oversight must also be meaningful. It is not enough to state that a human remains in the loop. The human reviewer must have authority to question, modify or reject algorithmic recommendations. Managers and HR professionals also need training to understand system limits. Without such competence, human review may become a ritual that legitimises system outputs rather than a genuine safeguard.

Voice mechanisms should be designed specifically for algorithmic HRM. Employees need channels to challenge data accuracy, request explanation, report exclusionary effects and appeal algorithmically influenced decisions. Organisations should also involve employees in system evaluation, particularly when tools affect monitoring, appraisal, scheduling or discipline. Such participation can reveal practical problems that technical audits may miss.

Finally, organisations should treat collective concerns as diagnostic rather than merely disruptive. If a group of employees challenges a monitoring or appraisal system, the issue may indicate a deeper design or governance problem. Listening to collective voice may help organisations detect bias, improve system legitimacy and avoid the normalisation of silent compliance.

11. Limitations and Future Research Directions

This paper is conceptual and therefore does not provide empirical evidence for the proposed relationships. The propositions require testing across organisational settings. Survey research could examine whether algorithmic control is associated with perceived autonomy, distributive justice, procedural justice, informational justice, inclusion, trust and different forms of voice. Longitudinal research would be especially valuable because employee trust may change as workers gain experience with algorithmic systems.

Qualitative research is also needed. Interviews and case studies could explore how employees interpret algorithmically influenced HR decisions, how managers use system outputs and how employees decide whether to speak or remain silent. Ethnographic work may be particularly useful in settings where monitoring and algorithmic evaluation are embedded in everyday routines. Such research could reveal how employees adapt to algorithmic control in practice.

Future studies should also examine boundary conditions. The effects of algorithmic HRM may vary by occupation, sector, employment status, union presence, regulatory environment, organisational climate and digital literacy. Platform work, professional services, healthcare, education, manufacturing and public administration may each produce different voice dynamics. Comparative research would help clarify when algorithmic HRM supports responsible governance and when it undermines employee agency.

Another research direction concerns the design of voice mechanisms. Scholars could examine which appeal systems, explanation practices, audit processes and participation mechanisms are most effective in building trust. It would also be useful to distinguish between trust in the technology, trust in HR professionals and trust in the organisation. These forms of trust may interact, but they are not identical.

12. Conclusion

Algorithmic HRM is reshaping the governance of work. Its significance lies not only in the speed or consistency of AI-enabled decisions, but also in how such decisions affect autonomy, justice, inclusion, trust and voice. This paper has argued that employees' responses to algorithmic HRM depend on whether systems preserve meaningful discretion, provide fair and explainable procedures, recognise diverse work realities and maintain accountable human oversight. Trust then becomes a key mechanism through which employees decide whether





to speak informally, use formal channels, act collectively or remain silent. A responsible approach to algorithmic HRM must therefore treat employee voice not as an optional employee-relations feature, but as a central condition of legitimate AI-enabled workplace governance.

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