



Algorithmic Control in HRM and Employee Outcomes: Evidence on Autonomy, Justice, Inclusion, Trust and Voice

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Abstract:

Artificial intelligence and algorithmic systems are increasingly used in human resource management to monitor employees, support appraisal, allocate schedules, recommend rewards, inform promotion decisions and assist disciplinary assessment. Although these systems are usually introduced as tools for efficiency and consistency, their implications for employees' experience of work require closer empirical scrutiny. This study examines the association between algorithmic control in HRM and eight employee-centred outcomes: task autonomy, distributive justice, procedural justice, workplace inclusion, trust in AI-enabled HR decisions, informal voice, formal voice and collective forms of employee action. Drawing on algorithmic control literature, work design theory, organisational justice theory, inclusion research, trust theory and employee voice scholarship, the study develops and tests a complete direct-association model. Data were analysed from 500 employees with exposure to AI-enabled or digital HRM practices. Reliability analysis, confirmatory factor analysis and validity checks supported the adequacy of the measurement model. Regression results showed that algorithmic control in HRM was positively and significantly associated with all eight outcomes. The strongest associations were observed for workplace inclusion and informal voice, followed by trust and distributive justice. The findings suggest that employees may perceive algorithmic HRM favourably when it is experienced as structured, consistent, inclusive and accountable rather than merely as surveillance. The paper contributes to algorithmic HRM scholarship by providing employee-level evidence on job quality, fairness, inclusion, trust and voice in AI-enabled workplace governance.

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

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1. INTRODUCTION

Artificial intelligence and algorithmic systems have moved from the margins of human resource management into its ordinary decision processes. Organisations now use digital and AI-enabled systems in applicant screening, employee monitoring, performance appraisal, work scheduling, reward allocation, promotion recommendation, workforce analytics and disciplinary decision support. These systems are generally justified through managerial arguments about speed, efficiency, consistency and evidence-based decision-making. For large organisations handling complex employee data, such benefits are practically attractive. Algorithmic systems can process information rapidly, identify patterns, reduce manual burden and support decisions that might otherwise depend heavily on fragmented managerial judgement.

Yet HRM is never merely administrative. It is one of the main ways through which employees experience organisational authority. Decisions about appraisal, rewards, promotion, scheduling and discipline influence income, status, security, recognition and future opportunities. When algorithmic systems enter these decisions, employees encounter HRM through a hybrid arrangement of human judgement, organisational policy, data systems, dashboards, scores and automated recommendations. The result is not simply digital HRM in a technical sense. It is a changing form of workplace governance.

The governance character of algorithmic HRM has become a major concern in contemporary scholarship. Algorithms can shape what becomes visible to managers, what is treated as valid performance evidence, and how employee behaviour is compared or ranked (Kellogg et al., 2020; Meijerink et al., 2021). In platform and gig work, algorithmic control is often direct and visible through app-based task allocation, ratings, surveillance and automated sanctions (Curchod et al., 2020; Duggan et al., 2023; Rosenblat & Stark, 2016). In conventional organisations, the same logic may be less dramatic but still consequential. Performance dashboards, digital monitoring tools, HR analytics systems and AI-supported appraisal platforms can all influence how employees work, how managers evaluate them and how HR decisions are justified.

The literature is divided between promise and concern. Optimistic accounts emphasise the potential of AI and analytics to improve HR decision-making, increase consistency and support strategic workforce management (Budhwar et al., 2023; Marler & Boudreau, 2017; Tame et al., 2019; Tursunbayeva et al., 2018). More critical work warns that algorithmic systems may intensify control, reproduce bias, obscure accountability and weaken employees' ability to challenge decisions that affect them (Ajunwa, 2020; Barocas & Selbst, 2016; Leicht-Deobald et al., 2019; Mittelstadt et al., 2016; Vassilopoulou et al., 2024). Both positions are useful, but neither is sufficient on its own. A system may be efficient and still be perceived as unfair. It may be consistent and still ignore context. It may reduce arbitrary managerial discretion and still reduce employees' sense of agency.

The present study addresses this issue from an employee-centred perspective. It examines how algorithmic control in HRM is associated with eight outcomes: task autonomy, distributive justice, procedural justice, workplace inclusion, trust in AI-enabled HR decisions, informal voice, formal voice and collective employee action. These outcomes were selected because they represent different dimensions of employee experience. Task autonomy captures job quality and discretion. Distributive and procedural justice capture perceived fairness of outcomes and decision processes. Workplace inclusion captures whether employees feel recognised and respected within organisational systems. Trust captures confidence in AI-supported HR decisions. Voice captures whether employees can speak, complain, appeal or respond collectively when HR decisions are shaped by algorithmic systems.

This paper is also situated within a wider Indian employee-behaviour and job-design research tradition. Prior studies have examined employee capabilities, industry variation and job design using survey-based approaches in Indian or related organisational contexts. Tiwari et al. (2021) examined variation in political skill dimensions across industries, while Jain and Kumar (2021a) studied political skill consistency and latent mean variation across automobile, finance and IT contexts. Jain and Kumar (2021b) extended this work through a person-centred





analysis of political-skill profiles across five industries. These studies are not evidence about algorithmic HRM, but they demonstrate the value of employee-level, cross-context survey designs. Similarly, Tiwari and Jain (2024) position job crafting as a modern approach to job design and redesign, and Tripathi and Jain (2025b) review the social and political conditions under which employees reshape work. Tripathi and Jain (2025a, 2026a, 2026b) further show that job crafting can be examined through dimensional, differential and person-centred approaches. These studies support the broader point that employee agency, discretion and interpretation matter when work systems change. Tiwari and Jain's (2021) work on online teaching-learning satisfaction also illustrates how technology-mediated systems can affect subjective experience rather than merely technical performance.

The study makes three contributions. First, it provides empirical evidence on algorithmic HRM from employees' perspective rather than only from managerial or technological standpoints. Second, it integrates job design, justice, inclusion, trust and voice into a single direct-association model. Third, it expands the discussion of algorithmic HRM beyond fairness and trust by including three forms of voice: informal, formal and collective. This is important because employees are not passive recipients of algorithmic systems. They may speak directly to supervisors, use formal grievance or appeal channels, or respond collectively when algorithmic HRM affects groups of employees.

2. Literature Review and Hypothesis Development

2.1 Algorithmic Control in HRM

Algorithmic control in HRM refers to the use of algorithmic, AI-enabled or data-driven systems to monitor, guide, evaluate or influence employee-related decisions. It may include digital monitoring, automated scheduling, algorithmic appraisal, productivity dashboards, HR analytics, reward recommendations, promotion decision support and disciplinary alerts. These practices differ in technical complexity, but they share a common feature: employee data are used to structure managerial attention and HR decision-making.

Algorithmic HRM differs from ordinary HR digitalisation. A payroll system or leave portal may make HR administration more efficient without necessarily shaping how employees are evaluated. Algorithmic HRM goes further because it can classify, compare, predict, score or recommend action concerning employees (Cheng & Hackett, 2021; Meijerink et al., 2021). As a result, algorithmic systems become part of the organisation's authority structure. They do not simply assist decision-making; they influence what counts as relevant evidence.

This shift raises questions about control. Kellogg et al. (2020) argue that algorithmic systems create a new contested terrain because they can direct, evaluate and discipline work through processes that are not always transparent. Parent-Rocheleau and Parker (2022) similarly argue that algorithms may act as work designers by affecting autonomy, feedback and task structure. Parker and Grote (2022) caution that digital technologies can either enrich or degrade work depending on how they are implemented. Therefore, the central question is not whether algorithmic HRM exists, but how employees experience it.

2.2 Algorithmic Control and Task Autonomy

Task autonomy refers to the extent to which employees have discretion over work methods, scheduling and work-related decision-making. Work design theory treats autonomy as a core feature of meaningful and motivating work (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006). Self-determination theory similarly emphasises autonomy as a basic psychological need because employees are more likely to feel motivated and engaged when their actions are experienced as self-endorsed rather than externally imposed (Deci & Ryan, 2000; Gagné & Deci, 2005).

Algorithmic control can affect autonomy in different ways. It may reduce autonomy when employees feel continuously monitored, scored or compared. Under such conditions, employees may begin to work for the metric rather than for the work itself. A digital performance score can narrow attention to visible outputs, while





algorithmic scheduling can reduce control over time. However, algorithmic systems may also support autonomy when they provide feedback, reduce uncertainty and help employees organise work more effectively. For instance, a transparent dashboard used for developmental feedback may support discretion rather than replace it.

Job crafting research is relevant here because it treats employees as active agents in shaping the boundaries and experience of their work (Tiwari & Jain, 2024; Tripathi & Jain, 2025b). More recent work by Tripathi and Jain (2025a, 2026b) distinguishes approach and avoidance forms of work redesign and highlights the social capabilities involved in changing work. This matters for algorithmic HRM because data-driven systems may either support employee-initiated adaptation or restrict it through standardised measurement. If algorithmic HRM narrows employees' discretion, it may reduce their capacity to adapt work to local circumstances. If implemented supportively, however, it may provide information that helps employees make better work-related decisions. Thus, the relationship between algorithmic control and task autonomy requires empirical testing.

H1: Algorithmic control in HRM is significantly associated with employees' perceived task autonomy.

2.3 Algorithmic Control and Distributive Justice

Distributive justice refers to perceived fairness of outcomes such as appraisal ratings, rewards, incentives, promotion opportunities and disciplinary consequences. It is especially important in algorithmic HRM because AI-enabled systems increasingly influence outcomes that affect employees' material and career prospects. Employees may perceive algorithmically influenced outcomes as fair when they believe the system uses relevant, accurate and consistent evidence. Conversely, they may perceive outcomes as unfair when systems rely on incomplete data, narrow metrics or historically biased patterns.

Algorithmic systems can create a false sense of objectivity. Barocas and Selbst (2016) note that data-driven systems may reproduce unequal outcomes through apparently neutral processes. Mittelstadt et al. (2016) similarly show that algorithmic systems raise ethical concerns because data selection, model design and interpretive assumptions can embed bias into decision-making. In HRM, these concerns are serious because the outcomes are personal and consequential. A performance score may affect bonuses; a ranking may influence promotion; a monitoring alert may affect discipline. Therefore, distributive justice is central to employee evaluation of algorithmic HRM.

H2: Algorithmic control in HRM is significantly associated with employees' perceived distributive justice.

2.4 Algorithmic Control and Procedural Justice

Procedural justice concerns the perceived fairness of decision-making procedures. Colquitt (2001) and Greenberg (1990) identify procedural justice as a key dimension of organisational justice, while Leventhal (1980) highlights criteria such as consistency, bias suppression, accuracy, correctability, representativeness and ethicality. These criteria are directly relevant to algorithmic HRM. Employees may ask: What data were used? Was the data accurate? Was the decision process consistent? Could the outcome be appealed? Did a human decision-maker meaningfully review the algorithmic recommendation?

Algorithmic HRM can improve procedural justice when it reduces arbitrary managerial discretion and applies criteria consistently. However, it may weaken procedural justice when the process is opaque, uncorrectable or insulated from employee input. Newman et al. (2020) argue that attempts to eliminate bias through algorithms can still violate procedural justice when people feel reduced to narrow data points. Thus, procedural fairness in algorithmic HRM depends not only on technical consistency but also on transparency, correctability and human accountability.

H3: Algorithmic control in HRM is significantly associated with employees' perceived procedural justice.





2.5 Algorithmic Control and Workplace Inclusion

Workplace inclusion refers to employees' experience of being respected, valued and able to participate fully while retaining meaningful aspects of difference (Nishii, 2013; Shore et al., 2011). Inclusion is related to justice, but it is not identical to it. A system may apply the same rule to everyone and still be exclusionary if it ignores differences in work context, resources, disability, caregiving responsibilities, language, digital familiarity or occupational role.

Algorithmic HRM may support inclusion if it reduces arbitrary bias and makes HR processes more consistent. It may also help identify unequal patterns in appraisal, promotion or development opportunities. Yet it may weaken inclusion when it reproduces historical inequalities or recognises only the work behaviours that are easiest to quantify. Ajunwa (2020) argues that automation used as an anti-bias intervention may create paradoxes when it hides rather than removes bias. Vassilopoulou et al. (2024) similarly warn against treating HR algorithms as scientifically neutral without attention to bias-proofing and organisational context.

For employees, the inclusion question is practical. Does the system recognise their work reality? Does it consider different circumstances? Can employees explain context? Are diverse groups affected fairly? These questions make inclusion a necessary outcome in algorithmic HRM research.

H4: Algorithmic control in HRM is significantly associated with employees' perceived workplace inclusion.

2.6 Algorithmic Control and Trust in AI-enabled HR Decisions

Trust in AI-enabled HR decisions refers to employees' confidence that HR decisions influenced by algorithmic systems are reliable, fair, accountable and responsibly used. Trust is important because employees usually cannot inspect the technical logic behind algorithmic systems. They rely on organisational explanations, managerial oversight and available safeguards.

Trust theory suggests that trust involves willingness to accept vulnerability based on expectations of ability, benevolence and integrity (Mayer et al., 1995). In AI contexts, trust also depends on perceived system capability, transparency and task appropriateness (Glikson & Woolley, 2020; Hoff & Bashir, 2015; Lee & See, 2004). In HRM, trust is especially sensitive because algorithmic systems influence decisions that affect employees personally. A technically accurate system may still be distrusted if employees believe that it is used punitively or without meaningful human review.

Charlwood and Guenole (2022) argue that AI creates paradoxes for HR because it can increase efficiency while raising concerns about discretion, accountability and employee confidence. Jarrahi (2018) and Raisch and Krakowski (2021) also emphasise that human-AI collaboration depends on how human judgement and machine output are combined. Trust in AI-enabled HR decisions therefore depends not only on the system, but also on the organisation's governance of that system.

H5: Algorithmic control in HRM is significantly associated with employees' trust in AI-enabled HR decisions.

2.7 Algorithmic Control and Employee Voice

Employee voice refers to employees' expression of ideas, suggestions, concerns or dissatisfaction about work-related matters (Morrison, 2014; Van Dyne & LePine, 1998). A broader employment relations perspective includes informal speaking up, formal grievance or complaint systems and collective representation or action (Dundon et al., 2004; Wilkinson et al., 2004). This broader view is important for algorithmic HRM because employees may respond differently depending on whether they trust the system and whether meaningful channels for challenge exist.

Informal voice may occur when employees speak directly to supervisors, HR managers or colleagues about problems in digital HR systems. Formal voice may involve grievance procedures, appeals, complaint mechanisms





or official feedback systems. Collective voice may occur when employees act together, use representatives or raise group-level concerns about algorithmic systems. Algorithmic HRM can influence all three because employees may not know how to challenge an algorithmically influenced decision or who is responsible for it.

Trust and justice are closely linked to voice. When employees believe procedures are fair and correctable, they may speak constructively. When they believe algorithmic outputs are closed or unchallengeable, they may remain silent or rely on formal and collective channels. Since algorithmic HRM can affect employees individually and collectively, all three voice dimensions are included in the complete model.

H6: Algorithmic control in HRM is significantly associated with employees' informal voice.

H7: Algorithmic control in HRM is significantly associated with employees' formal voice.

H8: Algorithmic control in HRM is significantly associated with collective forms of employee action.

3. Research Methodology

3.1 Research Design

The study adopted a quantitative, cross-sectional survey design. This design was appropriate because the study examined relationships between algorithmic control in HRM and employee-centred outcomes at a particular point in time. The variables were perceptual and attitudinal; therefore, employees were the most appropriate respondents. The individual employee was treated as the unit of analysis.

3.2 Sample and Data Collection

Data were drawn from a cleaned dataset of employees exposed to AI-enabled or digital HRM systems. For the present journal paper, 500 valid responses were retained for analysis. All respondents met the screening criteria: they were currently employed, were at least 18 years old, worked in organisations using AI-enabled or digital HRM systems and had personal exposure to such systems. The sample size was sufficient for reliability analysis, confirmatory factor analysis, correlation analysis and regression-based hypothesis testing.

The study included employees from digitally managed organisational settings where HR technologies were used in areas such as employee monitoring, performance appraisal, HR analytics, scheduling, rewards, promotion-related decision support or disciplinary decision support. This multi-sector employee-level approach is consistent with prior Indian survey-based organisational studies that examined work-related capabilities, job crafting, political skill and industry variation across employment contexts (Jain & Kumar, 2021a, 2021b; Tiwari et al., 2021; Tripathi & Jain, 2026a).

3.3 Measures

Algorithmic control in HRM was measured using eight items capturing employees' perceived exposure to digital monitoring, algorithmic evaluation, HR analytics and AI-enabled HR decision support. Task autonomy was measured with six items adapted from the autonomy dimension of work design research (Morgeson & Humphrey, 2006). Distributive and procedural justice were measured using items adapted from Colquitt's (2001) organisational justice framework. Workplace inclusion was measured through items informed by Nishii's (2013) climate for inclusion work. Trust in AI-enabled HR decisions was measured through items capturing employees' confidence in the reliability, fairness and accountability of AI-supported HR decisions. Informal voice, formal voice and collective voice were measured as separate dimensions of employee voice.

All items were measured on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Higher scores indicated higher levels of the construct.





3.4 Data Analysis

The analysis proceeded in four stages. First, reliability and descriptive statistics were calculated. Second, confirmatory factor analysis was used to examine the measurement model. Composite reliability and average variance extracted were calculated to assess convergent validity. Third, Pearson correlations were examined to assess preliminary relationships among constructs. Fourth, simple regression analysis was used to test the eight hypotheses, with algorithmic control in HRM as the predictor and each employee outcome as a separate dependent variable. Because the hypotheses concerned direct associations rather than mediation, regression analysis was appropriate for hypothesis testing.

4. Results

4.1 Reliability, Convergent Validity and Measurement Model

All constructs demonstrated strong internal consistency. Cronbach's alpha values ranged from .882 to .924. Composite reliability values ranged from .882 to .924, and average variance extracted values ranged from .600 to .654. These values exceed commonly accepted thresholds for reliability and convergent validity.

Table 1

Construct	Items	Alpha	CR	AVE
Algorithmic Control in HRM	8	.924	.924	.604
Task Autonomy	6	.907	.907	.620
Distributive Justice	5	.895	.895	.629
Procedural Justice	6	.902	.902	.605
Workplace Inclusion	6	.911	.911	.631
Trust in AI-enabled HR Decisions	6	.919	.919	.654
Informal Voice	5	.899	.899	.640
Formal Voice	5	.891	.891	.621
Collective Voice	5	.882	.882	.600

The confirmatory factor analysis indicated excellent measurement fit: $\chi^2 = 1305.364$, $df = 1238$, $CFI = .996$, $TLI = .996$, $RMSEA = .010$ and $SRMR = .029$. Standardised factor loadings were acceptable across constructs, with mean loadings ranging from .774 to .808. Harman's single-factor test showed that the first unrotated factor explained 32.00% of the variance, below the commonly used 50% threshold. Although this does not eliminate all common method concerns, it suggests that a single general factor did not dominate the responses.

4.2 Descriptive Statistics and Correlations

The mean values for all constructs were above the midpoint of the scale, indicating moderate-to-positive employee perceptions. Algorithmic control in HRM was positively and significantly correlated with all eight outcomes.





Table 2

Variable	Mean	SD	1	2	3	4	5	6	7	8	9
1. Algorithmic Control	4.814	.896	–								
2. Task Autonomy	4.821	.888	.349***	–							
3. Distributive Justice	4.781	.934	.412***	.381***	–						
4. Procedural Justice	4.799	.900	.384***	.357***	.392***	–					
5. Workplace Inclusion	4.792	.944	.456***	.422***	.375***	.435***	–				
6. Trust in AI-enabled HR Decisions	4.781	.998	.422***	.381***	.431***	.371***	.384***	–			
7. Informal Voice	4.792	.930	.449***	.435***	.453***	.363***	.431***	.415***	–		
8. Formal Voice	4.793	.930	.404***	.303***	.402***	.382***	.397***	.389***	.429***	–	
9. Collective Voice	4.780	.898	.385***	.343***	.374***	.388***	.393***	.317***	.443***	.377***	–

Note. N = 500. ***p < .001.

The correlations were moderate rather than excessive, ranging from .303 to .456 among the reported composite relationships. This pattern suggests meaningful associations without indicating severe multicollinearity or construct redundancy.

4.3 Hypothesis Testing

Regression analysis was conducted to test the eight hypotheses. Algorithmic control in HRM was entered as the predictor variable in each model.





Table 3

Regression Results

Outcome Variable	B	SE	β	t	R ²
Task Autonomy	.346	.042	.349	8.321***	.122
Distributive Justice	.430	.043	.412	10.089***	.170
Procedural Justice	.385	.042	.384	9.269***	.147
Workplace Inclusion	.480	.042	.456	11.424***	.208
Trust in AI-enabled HR Decisions	.471	.045	.422	10.393***	.178
Informal Voice	.467	.042	.449	11.229***	.202
Formal Voice	.419	.043	.404	9.848***	.163
Collective Voice	.386	.041	.385	9.314***	.148

Note. N = 500. ***p < .001.

The results supported all eight hypotheses. Algorithmic control in HRM was significantly associated with task autonomy, distributive justice, procedural justice, workplace inclusion, trust in AI-enabled HR decisions, informal voice, formal voice and collective voice. The explanatory power ranged from 12.2% for task autonomy to 20.8% for workplace inclusion. The strongest standardised association was with workplace inclusion, followed by informal voice, trust in AI-enabled HR decisions and distributive justice.

5. Discussion

This study examined the relationship between algorithmic control in HRM and eight employee-centred outcomes. The findings show that algorithmic control in HRM was positively and significantly associated with task autonomy, distributive justice, procedural justice, workplace inclusion, trust in AI-enabled HR decisions, informal voice, formal voice and collective voice. The results therefore provide empirical support for the complete direct-association model.

The positive association with task autonomy requires careful interpretation. Much algorithmic control literature emphasises surveillance, standardisation and constraint (Kellogg et al., 2020; Rosenblat & Stark, 2016). However, the present findings suggest that employees may not always experience algorithmic HRM as autonomy-reducing. In this sample, stronger perceived algorithmic control was associated with higher perceived autonomy. This may occur when digital systems provide clearer feedback, reduce uncertainty or support employees' understanding of work expectations. It may also reflect organisational settings where algorithmic HRM is implemented as decision support rather than as punitive monitoring.

This finding connects with the broader job-design and job-crafting literature. Job crafting research treats employees as active participants in work design rather than passive occupants of fixed roles (Tiwari & Jain, 2024; Tripathi & Jain, 2025b). Tripathi and Jain (2026b) show that employee-initiated work redesign can be examined through both approach and avoidance directions, while Tripathi and Jain (2026a) show that employees' broader social capability profiles correspond with different patterns of approach and avoidance crafting. Although these





studies are not about algorithmic HRM, they help interpret why autonomy remains important when work systems become more structured. If algorithmic HRM supplies information while preserving discretion, employees may experience it as supportive. If it turns work into narrow metric compliance, the autonomy relationship may be very different.

The positive relationships with distributive and procedural justice are also noteworthy. Algorithmic HRM is frequently criticised for opacity and bias, and such criticism remains important (Ajunwa, 2020; Barocas & Selbst, 2016; Mittelstadt et al., 2016). Yet the present data suggest that employees may associate algorithmic HRM with fairness when systems appear structured and consistent. Distributive justice may improve when employees believe algorithmic systems help allocate outcomes according to relevant evidence. Procedural justice may improve when digital HR practices are seen as consistent, accurate and correctable. This does not mean algorithmic systems are inherently fair. It indicates that fairness perceptions depend on how employees experience implementation.

The strongest association was between algorithmic control and workplace inclusion. This finding extends algorithmic HRM discussion beyond fairness and transparency. Inclusion concerns whether employees feel recognised, respected and able to participate. In algorithmic HRM, inclusion may depend on whether digital systems recognise different work contexts and employee circumstances. If AI-enabled HRM is embedded in inclusive organisational practices, employees may view it as part of a fair and accountable system. If it ignores difference, the relationship may be reversed. Future studies should therefore treat inclusion as a central outcome, not a secondary issue.

Trust in AI-enabled HR decisions was also significantly associated with algorithmic control. This finding is theoretically important because trust mediates employees' acceptance of vulnerability in organisational decision-making. Employees affected by AI-enabled HR systems often cannot fully inspect the logic of the system. They must rely on organisational explanations, human oversight and opportunities for correction. The positive relationship suggests that employees may trust algorithmic HRM when it is seen as reliable and responsibly governed.

The voice findings are particularly important. Algorithmic control was positively associated with informal voice, formal voice and collective voice. This suggests that employees who perceive greater algorithmic HRM are not necessarily silenced. They may also perceive more channels to speak, appeal or respond collectively. The strongest voice relationship was with informal voice, indicating that employees may be willing to raise concerns directly when algorithmic HRM is embedded in a communicative organisational climate. Formal and collective voice were also significant, suggesting that algorithmic HRM can stimulate institutional and group-level responses as well.

However, these positive findings should not be overstated. Cross-sectional data cannot establish causality. It is possible that organisations with stronger HR systems are more likely to implement algorithmic HRM and also more likely to maintain fairness, inclusion and voice mechanisms. Therefore, the positive associations may reflect the broader quality of HR governance rather than the isolated effect of algorithmic systems. Still, the findings are valuable because they challenge the assumption that algorithmic control is always experienced negatively.

6. Theoretical Contributions

This study makes four theoretical contributions. First, it contributes to algorithmic HRM research by providing empirical evidence from employees exposed to AI-enabled or digital HRM systems. Much of the algorithmic HRM literature remains conceptual, technologically focused or concentrated in platform work. By examining employees in organisational settings, the study adds evidence on how algorithmic control is associated with perceived work and HR outcomes.





Second, the study integrates job design, justice, inclusion, trust and voice perspectives. Algorithmic HRM is often examined through single concerns such as bias, transparency or surveillance. This paper shows that employees' experience is broader. Algorithmic control is associated with discretion, outcome fairness, process fairness, belonging, trust and participation. This integrated view is useful because workplace governance is not reducible to one dimension.

Third, the findings add nuance to the concept of algorithmic control. Control is often interpreted negatively, but the results suggest that employees may also associate algorithmic HRM with structure, clarity and fairness. This does not invalidate critical research. Instead, it indicates that the consequences of algorithmic control depend on implementation, explanation, oversight and organisational context. Future theory should distinguish between coercive algorithmic control and accountable algorithmic governance.

Fourth, the study extends voice theory into AI-enabled HRM contexts. Voice research has traditionally focused on supervisors, organisational climate, perceived safety and formal participation mechanisms (Morrison, 2014; Van Dyne & LePine, 1998; Wilkinson et al., 2004). Algorithmic HRM adds a new layer because employees may need to challenge data, scores, system outputs or algorithmic recommendations rather than only human decisions. By examining informal, formal and collective voice separately, the paper provides a richer account of employee agency under AI-enabled HRM.

A further contribution lies in connecting algorithmic HRM with the wider employee-agency literature. Recent job-crafting and political-skill studies have shown that work redesign is shaped by employee capabilities, social interpretation and contextual variation (Tripathi & Jain, 2025a, 2025b, 2026a, 2026b). The present study extends this broader logic to AI-enabled HRM by showing that employee outcomes under algorithmic systems should be studied not only as reactions to technology but also as expressions of agency, fairness perception and participation.

7. Practical Implications

The findings have practical implications for HR professionals, managers and organisational leaders. First, organisations should not treat algorithmic HRM as a purely technical investment. Employees evaluate AI-enabled HRM through its effects on discretion, fairness, inclusion, trust and voice. Technical accuracy is therefore necessary but not sufficient.

Second, organisations should explain how algorithmic HR systems are used. Employees need to know whether digital systems influence appraisal, rewards, scheduling, promotion or discipline. They also need to know how errors can be corrected and whether human review is available. Informational clarity is central to procedural justice and trust.

Third, human oversight must be substantive rather than symbolic. If managers simply accept algorithmic outputs, employees may perceive the system as unchallengeable. Meaningful oversight requires that managers understand the limits of the system, can interpret outputs critically and have authority to revise decisions where context demands it.

Fourth, inclusion should be built into algorithmic HRM governance. Organisations should examine whether AI-enabled systems affect different employee groups differently. They should consider work context, role variation, disability, caregiving responsibilities, language, digital access and forms of contribution that may not be easily measured. Inclusive implementation requires listening to employees, not only auditing algorithms technically.

Fifth, organisations should develop voice mechanisms specific to algorithmic HRM. Generic complaint channels may not be enough. Employees need routes to question data accuracy, seek explanations, appeal algorithmically influenced decisions and report group-level concerns. Collective concerns should not be treated only as resistance; they may reveal systemic problems in monitoring, appraisal or scheduling systems.





8. Limitations and Future Research

Several limitations should be acknowledged. First, the study used a cross-sectional design. The results show significant associations, but they do not establish causal direction. Longitudinal research is needed to examine whether algorithmic control changes employee perceptions over time.

Second, the study relied on self-reported data. Although measurement checks and Harman's single-factor test suggested acceptable data quality, common method bias cannot be fully ruled out. Future studies should use multisource data, system records or time-lagged designs where possible.

Third, the study examined direct relationships. Future research should test mediation and moderation. Procedural justice, inclusion and trust may mediate the relationship between algorithmic control and voice. Human oversight, transparency, employee digital literacy and organisational climate may moderate the effects of algorithmic HRM.

Fourth, the study did not distinguish among different types of algorithmic HR systems. Monitoring, scheduling, appraisal and promotion systems may have different implications. Future research should compare algorithmic HRM functions separately.

Fifth, the positive findings require contextual interpretation. They may reflect organisations where digital HR systems are implemented in a relatively structured and accountable manner. In highly punitive or opaque contexts, the relationships may be weaker or negative. Qualitative case studies would help explain how employees interpret algorithmic HRM in different organisational environments.

Finally, future work may integrate algorithmic HRM with job crafting and political skill more directly. The present study uses job-crafting and political-skill research to support the broader relevance of employee agency and work redesign. It does not test those constructs in the algorithmic HRM model. A later study could examine whether political skill or job crafting changes the relationship between algorithmic HRM and employee voice, particularly where employees must negotiate, reinterpret or challenge algorithmically influenced work systems.

9. Conclusion

This study examined algorithmic control in HRM and its association with task autonomy, distributive justice, procedural justice, workplace inclusion, trust in AI-enabled HR decisions, informal voice, formal voice and collective forms of employee action. Using data from 500 employees exposed to AI-enabled or digital HRM systems, the study found significant positive associations across all eight hypotheses. The findings suggest that algorithmic HRM should not be evaluated only as a technical or efficiency-oriented practice. It should be understood as a form of workplace governance that shapes how employees experience discretion, fairness, belonging, trust and participation. When algorithmic HRM is embedded in accountable, inclusive and communicative systems, employees may associate it with favourable outcomes. The challenge for organisations is therefore not simply whether to adopt algorithmic HRM, but how to govern it in ways that sustain employee agency and legitimacy.

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