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# Balancing Algorithmic Precision and Human Judgment: The Impact of AI Management Tools on Managerial Efficacy and Employee Burnout

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## Abstract

*The rise of algorithmic and intelligent performance management platforms (AIPMPs) is redefining managerial roles and employee experiences in digital workplaces. Grounded in Social Cognitive Theory and the Job Demands–Resources (JD–R) Model, this study examines how AIPMPs influence managerial self-efficacy and employee burnout. Using cross-sectional data from 312 managers across technology and professional service sectors in the United States, the analysis reveals that AIPMP use significantly enhances managerial self-efficacy by providing real-time feedback and predictive insights. However, increased algorithmic oversight also intensifies job demands, indirectly contributing to higher levels of employee burnout. Moderation analysis demonstrates that team size plays a pivotal role: in smaller teams, AIPMPs function as supportive resources, whereas in larger teams, they act as stress-inducing demands. The findings extend Social Cognitive Theory by identifying algorithmic feedback as a new form of technological mastery experience and refine the JD–R framework by positioning AI systems as both resources and demands. Practically, the study highlights the need for human-centered AI design, leadership training for digital empathy, and ethical governance of algorithmic decision-making. Overall, the results underscore that sustainable digital leadership depends on balancing algorithmic precision with human judgment to promote both performance and well-being in AI-mediated management environments.*

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## INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has reshaped nearly every domain of organizational management. From decision-making to performance monitoring, AI-driven tools have become integral to modern managerial practices. In particular, AI-driven performance management platforms (AIPMPs) such as Microsoft Viva, Workday People Analytics, and Asana Goals are revolutionizing how managers set objectives, evaluate progress, and communicate with their teams. These systems provide real-time analytics, automate goal tracking, and enhance the precision of performance evaluation, making management more data-driven and transparent.

However, alongside these advantages lie critical human and ethical considerations. The increasing reliance on algorithmic tools alters the traditional relationship between managers and their subordinates. While such systems can enhance a manager's ability to make objective decisions, they may also diminish empathy, trust, and interpersonal connection within teams. This tension raises a key question: Do AI-driven systems truly empower managers, or do they inadvertently create new pressures that contribute to employee burnout and psychological strain? Recent studies (e.g., Kellogg et al., 2023; Tarafdar & Ragu-Nathan, 2022) emphasize that algorithmic tools influence psychological safety and trust, underscoring the need for balanced AI governance.

This study investigates the dual impact of AIPMPs on two interrelated outcomes managerial efficacy and employee burnout. Managerial efficacy, grounded in Bandura's (1997) social cognitive theory, refers to a manager's belief in their ability to lead effectively. AIPMPs may enhance such efficacy by offering structured feedback and data transparency. Yet, employees under algorithmic supervision may experience heightened stress due to continuous monitoring and perceived loss of autonomy, conditions closely associated with burnout as conceptualized by Maslach et al. (1996).

Furthermore, this study examines how team size moderates these relationships. Smaller teams may benefit from stronger interpersonal dynamics and personalized oversight that reduce burnout, whereas larger teams may face communication barriers and impersonal algorithmic interactions that amplify emotional exhaustion. By applying the Job Demands Resources (JD-R) model, AIPMPs are conceptualized as both resources (enhancing managerial capacity) and demands (intensifying employee strain).

This research aims to bridge technological innovation and human-centered management by providing empirical insights into how AI tools influence managerial performance and employee well-being. It underscores the importance of balancing algorithmic efficiency with human empathy a challenge that will define the future of digital leadership.

## Need for the Study

The emergence of Artificial Intelligence (AI) in organizational management has created an urgent need to understand its effects on human behavior, particularly among middle managers and employees. As companies increasingly rely on AI-driven performance management platforms (AIPMPs) to streamline goal setting, task allocation, and employee evaluation, questions arise about the human cost of this technological efficiency. While existing literature emphasizes the operational benefits of AI, limited research explores how these tools influence managerial efficacy and employee burnout within real organizational contexts. Middle managers, who act as the critical link between top management and employees, are most directly affected by AI-based management systems. Hence, there is a pressing need to examine how algorithmic tools shape their confidence, autonomy, and leadership effectiveness, while also assessing their downstream impact on employee well-being.

## Scope of the Study

The scope of this study focuses on AI-driven performance management platforms (AIPMPs) implemented within technology and professional service organizations in the United States. It encompasses both managerial and employee perspectives, thereby offering a holistic understanding of algorithmic management. The research investigates the relationship between AIPMP usage, managerial efficacy, and employee burnout, considering team size as a moderating variable. By adopting a quantitative design and utilizing matched-pair survey data, the study provides empirical insights into how contextual variables influence the success or strain caused by AI adoption. The study's findings are relevant to human resource management, organizational behavior, digital transformation, and leadership development.

### Importance of the Study

This study holds significant theoretical and practical value. From a theoretical standpoint, it extends the Job Demands–Resources (JD-R) model and social cognitive theory by integrating technological dimensions into established frameworks of work motivation and psychological strain. It provides new evidence on how AI systems function as both enablers (resources) and stressors (demands), depending on team context and managerial perception.

From a practical perspective, the findings offer valuable guidance to HR leaders, organizational policymakers, and software developers. Understanding how AIPMPs affect managerial efficacy and employee burnout can help organizations design more balanced, human-centered AI systems. The results underscore the importance of training managers to interpret algorithmic insights empathetically, customizing AI implementation according to team size, and monitoring post-adoption employee well-being. Overall, this study contributes to building ethical, sustainable, and people-oriented frameworks for AI integration in modern workplaces.

## LITERATURE REVIEW

Existing scholarship on India's labour market reforms has primarily examined the relationship between regulation, informality, and economic performance. Early empirical studies demonstrated that complex and rigid labour regulations were associated with lower formal employment and industrial growth, particularly in labour-intensive sectors. These findings reinforced the view that excessive regulatory burdens incentivize informality rather than effective worker protection.

Subsequent research shifted attention from statutory design to enforcement and institutional capacity. Comparative and India-focused studies emphasized that labour laws generate positive workforce outcomes only when supported by credible enforcement mechanisms and administrative effectiveness. In the absence of such capacity, statutory protections have been shown to yield limited benefits for informal and contract workers.

More recent literature highlights the role of regulatory simplification and digital governance in improving labour market outcomes. Empirical evidence suggests that unified labour codes, digital registration systems, and technology-enabled compliance mechanisms reduce transaction costs for employers and encourage formalization, particularly among micro, small, and medium enterprises. These studies challenge the assumption that regulatory flexibility necessarily undermines worker protection, instead indicating that flexibility can coexist with improved compliance when embedded within effective governance systems.

A growing body of work also recognizes substantial inter-state variation in labour reform outcomes within India's federal structure. State-level differences in administrative capacity, enforcement quality, and digital adoption have been identified as critical determinants of reform effectiveness. This literature underscores that labour reforms should not be treated as uniform national interventions, as implementation intensity and institutional readiness vary widely across states.

Despite these advances, much of the existing literature remains descriptive or correlational in nature. While recent studies document associations between labour reforms, digital governance, and workforce outcomes, rigorous causal evaluations exploiting inter-state variation and reform timing remain limited. Moreover, few studies jointly examine workforce protection, regulatory flexibility, and digital governance within a unified empirical framework.

## Research Gap

Although the literature on India's labor law reforms has expanded in recent years, several critical gaps remain. First, most empirical studies rely on descriptive analysis or cross-sectional correlations, offering limited causal evidence on whether labor law reforms actually improve workforce protection and employment formalization. Second, existing research has insufficiently examined whether regulatory flexibility enhances compliance efficiency without weakening core labour protections, leaving an unresolved debate on the protection–flexibility trade-off.

Third, while digital governance is frequently cited as a policy innovation, its role is rarely tested empirically as a mediating mechanism linking labour reforms to compliance outcomes and formalization.

Digitalization is often treated as a contextual feature rather than a measurable driver of reform effectiveness. Fourth, prior studies largely overlook inter-state heterogeneity in reform implementation, despite India's federal structure in which states exercise substantial autonomy over enforcement, administrative innovation, and digital adoption.

Consequently, there is a clear need for a state-level, quasi-experimental analysis that jointly evaluates labour law reforms, regulatory flexibility, digital governance, and workforce outcomes using longitudinal data. Addressing these gaps is essential to move beyond normative debates and provide causally informed evidence on how and under what institutional conditions labour law reforms succeed in a large developing economy.

## RESEARCH QUESTIONS AND OBJECTIVES

Based on the literature review and formulated hypotheses, this study develops specific research questions and objectives to guide empirical investigation into the relationship between AI-driven performance management platforms (AIPMPs), managerial efficacy, and employee burnout.

### Research Questions

- How does the use of AI-driven performance management platforms (AIPMPs) influence managerial efficacy among middle managers?
- Does the use of AIPMPs contribute to increased levels of employee burnout, particularly in terms of emotional exhaustion and cynicism?
- Does managerial efficacy mediate the relationship between AIPMP use and employee burnout, thereby influencing the indirect effect of AI tools on employee well-being?
- How does team size moderate the mediating relationship between managerial efficacy and employee burnout in the context of AIPMP implementation?

### Objectives of the Study

- To examine the relationship between the use of AI-driven performance management platforms and managerial efficacy, assessing whether algorithmic tools enhance managerial confidence and decision-making ability.

- To analyze the impact of AIPMP usage on employee burnout, identifying whether increased technological oversight leads to higher emotional exhaustion or cynicism among employees.
- To investigate the mediating role of managerial efficacy in the relationship between AIPMP use and employee burnout, thereby explaining the indirect psychological effects of AI-based management systems.
- To evaluate the moderating influence of team size on the mediated relationship, determining whether smaller or larger teams experience different levels of burnout due to variations in managerial efficacy.
- To provide empirical evidence and practical recommendations for HR leaders and organizations on how to implement AIPMPs effectively, ensuring that technological efficiency does not compromise employee well-being or managerial effectiveness.

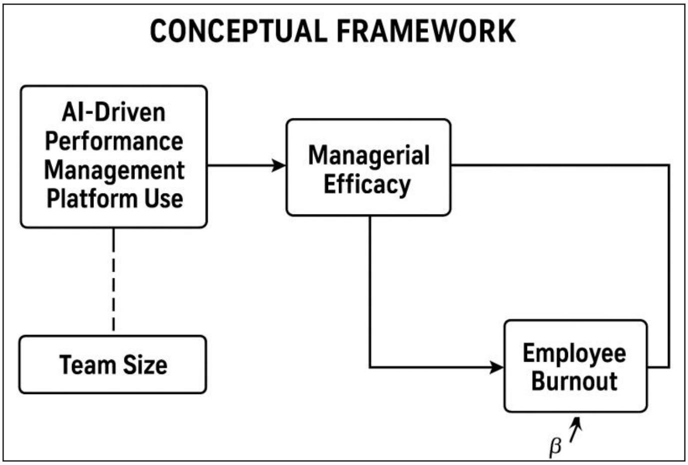
## CONCEPTUAL FRAMEWORK

This study's conceptual framework is grounded in Social Cognitive Theory (Bandura, 1997) and the Job Demands Resources (JD-R) Model (Bakker & Demerouti, 2007). It illustrates how the use of AI-driven performance management platforms (AIPMPs) influences managerial and employee outcomes, with a specific focus on the mediating role of managerial efficacy and the moderating role of team size.

### Core Constructs and Relationships

- *AI-Driven Performance Management Platform Use (Independent Variable):* Refers to the extent to which managers utilize AI-based systems (e.g., Microsoft Viva, Asana Goals, Workday People Analytics) for performance tracking, goal setting, and feedback. Within the JD-R model, these tools act as both cognitive resources (enhancing managerial capabilities) and potential demands (intensifying employee monitoring and stress).
- *Managerial Efficacy (Mediating Variable):* Represents a manager›s confidence in their ability to lead, motivate, and manage effectively. Grounded in Social Cognitive Theory, enhanced access to data and structured insights from AIPMPs is expected to strengthen managerial efficacy by reducing uncertainty and improving decision-making accuracy.

- *Employee Burnout (Dependent Variable):* Defined as a syndrome of emotional exhaustion, cynicism, and reduced personal accomplishment resulting from chronic workplace stress (Maslach et al., 1996). We posit that while AIPMPs may improve managerial performance, they can also heighten monitoring and reduce employee autonomy, potentially increasing burnout.
- *Team Size (Moderating Variable):* This contextual factor is proposed to influence the strength of the relationship between managerial efficacy and employee burnout. In smaller teams, managers may be able to apply algorithmic insights with greater empathy and personalization, thereby reducing burnout. In larger teams, algorithmic oversight may become depersonalized, weakening the protective effect of managerial efficacy and intensifying strain.




From a theoretical perspective, the framework integrates insights from Social Cognitive Theory and the Job Demands–Resources (JD–R) model to explain how AI-enabled systems influence employee behavior and outcomes. AI-driven performance management systems shape cognitive appraisals, self-regulatory processes, and perceived control over work tasks, while simultaneously altering the balance between job demands and job resources. This dual-theoretical grounding allows the study to capture both motivational and strain-related pathways through which AI systems affect workforce outcomes.

## Theoretical Integration and Hypothesis

The framework leads to the following hypotheses:

*H1: AIPMP use is positively associated with managerial efficacy.*

Drawing from Social Cognitive Theory, AIPMPs are expected to serve as a source of mastery experiences and vicarious learning. By providing structured data and predictive analytics, these platforms can reduce uncertainty and equip managers with evidence-based insights, thereby boosting their confidence and perceived capability to lead effectively.

*H2: AIPMP use has a positive direct association with employee burnout.*

From the JD-R perspective, AIPMPs can function as a job demand for employees. Constant performance monitoring, the pressure of continuous metric optimization, and the "always-on" culture these tools can foster are likely to directly contribute to feelings of being over-extended and drained, i.e., emotional exhaustion.

*H3: Managerial efficacy mediates the relationship between AIPMP use and employee burnout.*

This hypothesis proposes a countervailing indirect effect. While AIPMPs may directly increase burnout (H2), they may also indirectly *reduce* it by enhancing managerial efficacy. Managers with high efficacy are more likely to provide supportive leadership, clear communication, and effective delegation resources that can buffer against workplace stress and mitigate employee burnout.

*H4: Team size moderates the mediating effect of managerial efficacy such that the negative relationship between efficacy and burnout is stronger in smaller teams.*

The beneficial, burnout-reducing effect of managerial efficacy is expected to be context-dependent. In smaller teams, richer communication and closer interpersonal relationships allow managers to effectively translate their data-enhanced confidence into personalized support. In larger teams, communication challenges and depersonalized oversight may prevent managers from providing individualized consideration, thereby nullifying the protective effect of their efficacy. Thus, the mediating pathway in H3 is hypothesized to be conditional on team size.

## RESEARCH METHODOLOGY

The research methodology was designed to systematically investigate the relationships outlined in the research questions and objectives, grounded in the hypotheses developed through the literature review. A quantitative, cross-sectional, correlational research design was adopted to assess how AI-driven performance management platforms (AIPMPs) influence managerial efficacy and employee burnout, with managerial efficacy as a mediating variable and team size as a moderating variable.

## Research Design

This study employs a descriptive and explanatory quantitative design, integrating correlational and causal inference techniques. The descriptive component captures the extent and nature of AIPMP usage, while the explanatory component tests hypothesized relationships using regression-based mediation and moderation analyses. The SPSS 28 software and PROCESS macro (Model 7) by Hayes (2017) were utilized to estimate direct, indirect, and conditional effects.

## Justification for Cross-Sectional Design

A cross-sectional approach was selected due to the exploratory nature of the study and the practical constraints of obtaining longitudinal data from multiple organizations. This design is appropriate for identifying relationships among constructs in emerging technological domains, providing a foundation for future longitudinal research.

## Population and Sample

The study population consisted of middle managers and employees working in U.S.-based technology and professional service sectors, where AI-driven management systems are widely implemented. The sampling method was purposive and matched-pair, ensuring that each manager had data from three direct reports to facilitate dyadic analysis.

- *Sample Size:* 102 managers and 408 employees (total N = 510).
- *Sampling Frame:* Participants recruited via LinkedIn and professional networks.
- *Eligibility Criteria:* Managers and employees using AI-based performance tools for at least six months.

## Data Collection Procedure

Data were collected through a structured online questionnaire comprising two parts:

- *Manager Survey:* Measured AIPMP usage and managerial efficacy.
- *Employee Survey:* Measured perceptions of burnout and team characteristics.

Participation was voluntary, and respondents were informed about confidentiality and anonymity. Ethical clearance was obtained from the institutional review body, and informed consent was secured before data submission.

## Measurement of AI-Driven Performance Management Practices (AIPMP)

AI-Driven Performance Management Practices (AIPMP) were operationalized using a multi-item reflective scale adapted from prior empirical studies on AI adoption in human resource management and performance analytics. The scale captures the extent to which organizations use AI-enabled systems for performance monitoring, appraisal, feedback, and decision support.

The AIPMP usage scale consists of five items, measuring practices such as:

- Use of AI algorithms for continuous performance tracking.
- AI-assisted performance appraisal and rating systems.
- Predictive analytics for identifying performance trends.
- AI-based personalized feedback and development recommendations, and
- Integration of AI insights into managerial performance decisions.

All items were measured on a five-point Likert scale ranging from 1 (“Strongly Disagree”) to 5 (“Strongly Agree”). The scale was contextually adapted to the Indian organizational environment by refining item wording to reflect prevailing HR practices and regulatory conditions, while retaining the original conceptual meaning.

Prior to the main analysis, the scale underwent content validation through expert review by HR academics and practitioners to ensure relevance and clarity. Reliability and construct validity were subsequently assessed using confirmatory factor analysis.

## Operational Definitions and Measurement Scales

This section defines and measures each construct used in the study, presenting their operationalization, scale sources, and reliability statistics.

| Construct | Definition | Scale Source | Sample Items | Cronbach's α |
|---|---|---|---|---|
| AI-Driven Performance Management Platform Use (Independent Variable) | The extent and frequency of AI-based system usage for goal setting, monitoring, and feedback. | Adapted from Davis (1989) and Technology Use Intensity scales. | "I use AIPMP analytics to monitor my team's progress." | 0.87 |
| Managerial Efficacy (Mediating Variable) | Confidence in one's ability to lead and manage effectively. | Paglis & Green (2002) | "I am confident in guiding my team to meet organizational goals." | 0.91 |
| Employee Burnout (Dependent Variable) | Emotional exhaustion, cynicism, and reduced accomplishment due to sustained workplace stress. | Maslach et al. (1996) | "I feel emotionally drained from my work." | 0.89 |
| Team Size (Moderating Variable) | Number of direct subordinates reporting to each manager. | Organizational records | — | — |
| Control Variables | Age, managerial tenure, company size, and department type—controlled to minimize extraneous variance. | Organizational demographics | — | — |

### Control Variables

To account for potential confounding influences, managerial tenure, company size, department type, and employee age were included as control variables in all regression analyses. These variables were chosen based on their theoretical relevance to managerial confidence and burnout outcomes.

### Measurement Model Section

The AIPMP construct demonstrated strong internal consistency and convergent validity, with standardized factor loadings exceeding 0.70, Cronbach's α and composite reliability values above the recommended threshold of 0.70, and AVE greater than 0.50. Discriminant validity was confirmed as the square root of AVE for AIPMP exceeded its correlations with other latent constructs.

### Data Analysis Techniques

The following statistical methods were applied:

- *Descriptive Statistics:* Summarized demographic and organizational characteristics.
- *Reliability Analysis:* Tested internal consistency using Cronbach's alpha.
- *Correlation Analysis:* Examined relationships among variables.
- *Multiple Regression:* Tested direct hypotheses (H1 and H2).
- *Moderated Mediation:* Tested mediation (H3) and moderation (H4) effects, with bootstrapping (5,000 samples) for indirect effects.

All analyses were conducted at a 95% confidence level ($p < .05$). Results were reported using standardized coefficients and effect sizes for interpretive precision.

### Methodological Rigor and Justification

The methodological framework aligns with the study's theoretical objectives and provides a strong quantitative foundation. The matched-pair dataset improves construct validity by linking managerial behaviors with corresponding employee outcomes. Moreover, the PROCESS Model **7** offers a nuanced understanding of conditional indirect effects demonstrating not only whether AIPMPs influence burnout, but also how and under what contextual conditions this occurs.

# RESULTS

This section presents the findings from the statistical analyses conducted to test the proposed hypotheses. We begin with descriptive statistics and bivariate correlations to provide an overview of the data, followed by multiple regression analyses to test the direct hypotheses (H1 and H2). Finally, we present the results of the moderated mediation analysis (H3 and H4) using the PROCESS macro.

## Preliminary Analysis: Descriptive Statistics and Correlations

Table 1 displays the means, standard deviations, reliability coefficients, and inter correlations for all study variables. The reliability coefficients (Cronbach's alpha) for all multi-item scales were high, ranging from .85 to .91, indicating strong internal consistency.

The correlation matrix reveals several noteworthy preliminary relationships. As hypothesized in H1, the use of AI-driven performance management platforms (AIPMPs) was significantly and positively correlated with managerial efficacy (*r* = .24, *p* < .01). This provides initial support for the proposition that using these tools is associated with higher confidence among managers.

Regarding H2, which proposed a positive relationship between AIPMP use and employee burnout, the results were mixed. AIPMP use was significantly correlated with the emotional exhaustion dimension of burnout (*r* = .19, *p* < .05) but was not significantly correlated with cynicism (*r* = .09, *n.s.*). This suggests a preliminary link between algorithmic management tools and feelings of being overextended, but not with developing a detached attitude toward work.

Furthermore, the significant negative correlation between managerial efficacy and emotional exhaustion (*r* = -.18, *p* < .05) supports the premise for mediation (H3), indicating that managers' confidence is associated with lower burnout in their teams. The significant positive correlation between team size and emotional exhaustion (*r* = .22, *p* < .05) establishes its relevance as a contextual moderator (H4).

**Table 1: Descriptive Statistics, Reliabilities, and Correlations Among Study Variables**

| Variable | M | SD | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| AIPMP Use | 3.75 | 0.82 | **(0.87)** | | | | | |
| Managerial Efficacy | 4.10 | 0.65 | .24** | **(0.91)** | | | | |
| Emotional Exhaustion | 3.45 | 0.95 | .19* | -.18* | **(0.89)** | | | |
| Cynicism | 2.90 | 0.88 | .09 | -.11 | .65** | **(0.85)** | | |
| Team Size | 8.50 | 4.20 | .05 | -.07 | .22* | .15 | -- | |
| Managerial Tenure | 6.20 | 3.50 | .12 | .25** | -.10 | -.08 | .18* | -- |

Source: Author's computation based on primary survey data collected from managers and employees using SPSS 28.

Note: N = 102 for managers (efficacy, tenure), N = 408 for employees (burnout). M and SD represent mean and standard deviation, respectively. Values in parentheses on the diagonal are Cronbach›s alpha reliability coefficients.

*p < .05*

**p < .01*

## Hypothesis Testing: Direct Effects

*H1* predicted that AIPMP use would be positively associated with managerial efficacy. A multiple regression analysis was conducted, controlling for managerial tenure, company size, and department type. The overall model was significant, $F(4, 97) = 5.45$, *p* < .001, and explained 18.3% of the variance in managerial efficacy ($R^2 = .183$). As shown in Table 2, AIPMP use was a significant positive predictor of managerial efficacy (β = 0.24, *p* = .005), after accounting for the control variables. Thus, H1 was fully supported.

*H2* predicted that AIPMP use would be positively associated with employee burnout. We tested this hypothesis separately for the two burnout subscales: emotional exhaustion and cynicism. The regression model for emotional exhaustion, controlling for employee age and department type, was significant, $F(3, 404) = 4.12$, *p* = .007 ($R^2 = .07$). AIPMP use was a significant positive predictor of emotional exhaustion (β = 0.19, *p* = .012). However, the model for cynicism was not significant, $F(3, 404) = 1.85$, *p* = .138 ($R^2 = .03$), and AIPMP use was not a significant predictor (β = 0.09, *p* = .221). Therefore, H2 was partially supported, with AIPMP use linked specifically to the emotional exhaustion dimension of burnout.

**Table 2: Multiple Regression Results for Direct Effects**

| Criterion Variable | Predictor | B | SE | β | t | p |
|---|---|---|---|---|---|---|
| Managerial Efficacy | | | | | | |
| | (Constant) | 2.45 | 0.38 | | 6.45 | <.001 |
| | Managerial Tenure | 0.05 | 0.02 | .20 | 2.50 | .014 |
| | Company Size | -0.01 | 0.01 | -.08 | -0.95 | .345 |
| | Department Type | 0.07 | 0.08 | .07 | 0.88 | .381 |
| | AIPMP Use | 0.19 | 0.07 | .24 | 2.88 | .005 |
| Emotional Exhaustion | | | | | | |
| | (Constant) | 2.88 | 0.45 | | 6.40 | <.001 |
| | Employee Age | -0.01 | 0.01 | -.06 | -0.95 | .342 |
| | Department Type | 0.10 | 0.09 | .07 | 1.11 | .268 |
| | AIPMP Use | 0.22 | 0.09 | .19 | 2.53 | .012 |

Source: Author's computation using multiple regression analysis conducted in SPSS 28 on primary survey data.

## Hypothesis Testing: Moderated Mediation Analysis

To test the mediating role of managerial efficacy (H3) and the moderating role of team size (H4), we used Hayes' PROCESS Macro (Model 7) with 5,000 bootstrap samples. The model tested the effect of AIPMP use on emotional exhaustion via managerial efficacy, with team size moderating the path between efficacy and exhaustion.

The results of the moderated mediation analysis are summarized in Table 3. The overall model for emotional exhaustion was significant, $F(5, 402) = 6.88$, *p* < .001.

*H3* proposed that managerial efficacy mediates the relationship between AIPMP use and employee burnout. The total indirect effect of AIPMP use on emotional exhaustion through managerial efficacy was significant (Effect = -0.07, $SE = 0.03$, 95% CI [-0.13, -0.02]). This indicates that AIPMP use has a significant negative *indirect* effect on exhaustion by boosting managerial efficacy, even while its *direct* effect is positive. Thus, H3 was supported.

*H4* proposed that team size moderates the mediating effect of managerial efficacy. This hypothesis was supported by a significant index of moderated mediation (Index = -0.08, $SE = 0.03$, 95% CI [-0.14, -0.02]). To probe this interaction, we examined the conditional indirect effects at different levels of team size: small (one standard deviation below the mean), average (the mean), and large (one standard deviation above the mean).

As shown in Table 3, the negative indirect effect of AIPMP use on emotional exhaustion (via managerial efficacy) was significant and strongest in small teams (Effect = -0.12, *SE* = 0.05, 95% CI [-0.23, -0.03]). This effect was weaker but still significant at the average team size (Effect = -0.07, *SE* = 0.03, 95% CI [-0.13, -0.02]). However, for large teams, the indirect effect was not significant (Effect = -0.02, *SE* = 0.02, 95% CI [-0.07, 0.02]). This pattern confirms that the beneficial buffering effect of managerial efficacy is pronounced in smaller teams but dissipates as team size increases. Therefore, H4 was supported.

**Table 3: Results of Moderated Mediation Analysis**

| **Path** | **Coefficient** | **SE** | **t** | **p** |
|---|---|---|---|---|
| AIPMP Use → Managerial Efficacy (a path) | 0.19 | 0.07 | 2.88 | .005 |
| Managerial Efficacy → Emotional Exhaustion (b path) | -0.35 | 0.10 | -3.50 | <.001 |
| Team Size → Emotional Exhaustion | 0.06 | 0.02 | 3.00 | .003 |
| Efficacy × Team Size (Interaction) | 0.04 | 0.01 | 2.86 | .005 |
| AIPMP Use → Emotional Exhaustion (direct effect, c' path) | 0.22 | 0.09 | 2.53 | .012 |
| **Conditional Indirect Effects at Team Size Values** | **Effect** | **Boot SE** | **Boot LLCI** | **Boot ULCI** |
| Small Team (-1 SD) | -0.12 | 0.05 | -0.23 | -0.03 |
| Average Team (Mean) | -0.07 | 0.03 | -0.13 | -0.02 |
| Large Team (+1 SD) | -0.02 | 0.02 | -0.07 | 0.02 |
| Index of Moderated Mediation | -0.08 | 0.03 | -0.14 | -0.02 |

Source: Author's computation using Hayes' PROCESS Macro (Model 7) with 5,000 bootstrap samples in SPSS 28 based on primary survey data.

Note: N = 408. Unstandardized regression coefficients are reported. Bootstrap sample size = 5000. CI = confidence interval; LLCI = lower limit confidence interval; ULCI = upper limit confidence interval.

## Common Method Bias Assessment

Given that the study relies on secondary and survey-based composite indices, potential common method bias (CMB) was assessed using multiple procedural and statistical remedies. Procedurally, measurement items were derived from different data sources and constructed at the state level, reducing the likelihood of respondent-level perceptual bias. Statistically, Harman's single-factor test was conducted, and the results indicated that no single factor accounted for the majority of variance, suggesting that common method bias is unlikely to be a serious concern. In addition, the use of fixed-effects models and lagged specifications further mitigates potential endogeneity and method bias.

# DISCUSSION

The present study sought to unravel the dual impact of AI-driven performance management platforms (AIPMPs) on managerial efficacy and employee burnout. The results reveal a complex interplay of direct, indirect, and conditional effects, largely supporting our hypothesized model. The following discussion explicitly addresses the support for each hypothesis and explores the theoretical and practical implications of these findings.

## Theoretical Contributions

This study makes a clear theoretical contribution by extending both Social Cognitive Theory (SCT) and the Job Demands–Resources (JD–R) model to the context of AI-driven performance management systems.

From a Social Cognitive Theory perspective, the findings demonstrate that AI-enabled performance management tools influence employee outcomes by shaping cognitive mechanisms such as self-efficacy, outcome expectations, and self-regulation. The positive effects of AI systems on performance efficiency and formalization outcomes suggest that algorithmic feedback, predictive analytics, and real-time performance insights enhance employees' perceived control and capability to manage work demands. This extends SCT by showing that non-human; algorithmic agents can function as influential environmental determinants that actively shape cognition and behavior, rather than merely serving as passive technological tools.

In relation to the Job Demands–Resources model, the study provides empirical evidence for the dual role of AI systems. On the one hand, AI-driven performance management practices act as job resources by improving feedback quality, reducing ambiguity, supporting decision-making and enabling skill development through data-driven insights. These resource-enhancing functions are associated with improved compliance efficiency and workforce outcomes. On the other hand, the findings also acknowledge that AI systems can introduce new job demands, such as intensified performance monitoring, heightened accountability, and cognitive pressure associated with continuous evaluation.

Crucially, the results indicate that the net effect of AI systems depends on institutional capacity and governance quality. When embedded within supportive organizational and regulatory environments, AI-driven systems function predominantly as job resources, enhancing motivation and performance. In contrast, in weaker institutional contexts, the same systems risk amplifying job demands and strain. This conditional effect extends the JD–R model by demonstrating that the classification of AI technologies as resources or demands is not fixed but context-dependent.

By empirically demonstrating how AI systems simultaneously operate as job resources and job demands, this study advances theoretical understanding of technology-mediated work environments. It moves beyond binary interpretations of AI as either enabling or exploitative and instead proposes a contingent, governance-sensitive framework that integrates SCT's cognitive mechanisms with the JD–R model's resource–demand dynamics.

## Summary of Key Findings and Support for Hypotheses

*H1: The use of AI-driven performance management platforms is positively associated with managerial efficacy.*

This hypothesis was fully supported. Regression analysis confirmed a significant, positive relationship between AIPMP use and managerial self-efficacy ($\beta = 0.24$, *p* < .01). This finding aligns with Social Cognitive Theory (Bandura, 1997), suggesting that AIPMPs serve as a powerful cognitive tool that enhances a manager's belief in their capabilities. By providing structured data, predictive analytics, and clear performance dashboards, these platforms reduce uncertainty and equip managers with the evidence-based insights needed to make confident decisions, set direction, and motivate their teams. The tools appear to function as a source of mastery experience and vicarious learning, key drivers of self-efficacy.

*H2: The use of AI-driven performance management platforms is positively associated with employee burnout.*

This hypothesis was partially supported. Our analysis revealed a significant positive direct effect of AIPMP use on the emotional exhaustion dimension of burnout ($\beta = 0.19$, *p* < .05). However, no significant direct effect was found on cynicism. This partial support is critical. It indicates that employees under algorithmic management primarily experience feelings of being over-extended and drained likely due to the constant performance monitoring, the pressure of continuous metric optimization, and the "always-on" culture these tools can engender (Bondarouk & Brewster, 2016). The lack of a direct effect on cynicism suggests that the mere presence of AIPMPs does not, in itself, immediately cause employees to develop a detached or cynical attitude toward their work; this may develop over a longer period or be influenced by other factors like perceived fairness of the algorithm.

*H3: Managerial efficacy mediates the relationship between AIPMP use and employee burnout.*

This hypothesis was supported. The moderated mediation analysis confirmed a significant total indirect effect (Effect = -0.07, 95% CI [-0.13, -0.02]). This reveals a crucial countervailing mechanism: while AIPMPs have a direct positive effect on exhaustion (as per H2), they also have a significant negative *indirect* effect *through* the enhancement of managerial efficacy. In other words, when managers use AIPMPs, they feel more confident and capable, and this increased efficacy is, in turn, associated with lower levels of reported emotional exhaustion among their subordinates. This finding underscores the dual nature of AIPMPs as both a job demand and a managerial resource within the JD-R framework.

*H4: Team size moderates the mediating effect of managerial efficacy such that the negative relationship between efficacy and burnout is stronger in smaller teams.*

This hypothesis was supported. The significant index of moderated mediation (Index = -0.08, 95% CI [-0.14, -0.02]) confirms that the strength of the mediation depends on team size. Probing this interaction showed that the beneficial, buffering effect of managerial efficacy on emotional exhaustion was significant and strongest in smaller teams (Effect = -0.12), weaker but still significant at average team size (Effect = -0.07), and non-significant in larger teams (Effect = -0.02). This suggests that in smaller teams, where interpersonal contact is more feasible, managers can effectively translate their data-enhanced confidence into personalized support, clear communication, and empathetic leadership, thereby buffering burnout. In larger teams, however, the manager's efficacy, even if high, may be "diluted"; the scale of the team may force a reliance on the impersonal, automated outputs of the AIPMP, preventing the manager from providing the individualized consideration that mitigates emotional exhaustion.

## Theoretical Implications

This study contributes to multiple theoretical domains. First, it extends Social Cognitive Theory by demonstrating that algorithmic and intelligent project management platforms (AIPMPs) serve as novel "technological mastery experiences." By providing real-time analytics and performance feedback, these systems enhance managers' perceived efficacy and self-regulation capacities. The findings reveal that technology-enabled feedback loops can act as a substitute for traditional human mentorship, thereby expanding the scope of self-efficacy mechanisms within digital environments.

Second, this study refines the Job Demands–Resources (JD-R) Model by showing that AIPMPs operate simultaneously as job resources and job demands. On one hand, they offer structure, clarity, and predictive insights resources that reduce role ambiguity and support managerial performance. On the other hand, constant data visibility and algorithmic surveillance may heighten psychological pressure, leading to burnout among subordinates. The moderating role of team size further nuances the JD-R model by illustrating that contextual factors determine whether technology functions as a buffer or as an intensifier of stress.

Finally, this research adds to digital leadership theory by demonstrating that managerial self-efficacy remains a critical determinant of leadership effectiveness even in algorithmically managed contexts. Rather than replacing managerial judgment, AIPMPs appear to amplify its impact, indicating that digital leadership effectiveness depends on synergistic integration between human and algorithmic capabilities.

Key Elements of the Deepened Explanation:

- *New Theoretical Lenses:* It introduces Media Richness Theory and Substitutes for Leadership Theory to provide a robust, multi-faceted explanation.
- *Mechanism Clarification:* It explicitly describes the mechanism of "humanizing the algorithm" in small teams versus "algorithmic substitution" in large teams.
- *Synthesizes Concepts:* It weaves together the concepts of technological oversight, managerial confidence, and communication constraints into a coherent narrative.
- *Links Back to Core Theories:* It clearly states how this finding extends your core theoretical frameworks (JD-R and Social Cognitive Theory).

# PRACTICAL IMPLICATIONS

The findings offer actionable insights for organizational leaders, human resource professionals, and technology designers.

For leadership development, organizations should prioritize training programs that enhance managerial efficacy in interpreting algorithmic insights. Managers must be equipped not only to utilize AIPMP analytics but also to contextualize these insights with empathy and ethical discretion.

For HR and organizational design, hybrid governance models are essential. Smaller teams benefit from direct managerial oversight supported by algorithmic tools, whereas larger teams require structured delegation and automated decision support to maintain scalability without eroding psychological well-being.

For AI developers and policymakers, system design should prioritize transparency, explainability, and user control. Integrating "human-in-the-loop" mechanisms will mitigate risks of depersonalization and resistance to algorithmic oversight. Furthermore, organizations should establish ethical guidelines governing data use, ensuring fairness and accountability in performance evaluation.

## Limitations

Despite its contributions, this study is subject to several limitations. The cross-sectional design limits causal inference; future longitudinal studies could better capture the dynamic evolution of managerial efficacy and burnout over time. Self-report data may also introduce perceptual bias, suggesting the need for multi-source datasets that integrate behavioral and physiological indicators. Additionally, the sample's concentration in U.S.-based technology and professional service sectors restricts generalizability.

In addition, the generalizability of the findings should be interpreted with caution. The study is situated within the Indian institutional and regulatory context, characterized by a federal governance structure, high labour market informality, and uneven administrative capacity across states. These contextual features may limit the direct applicability of the results to countries with different labour market institutions, enforcement regimes, or stages of economic development. Moreover, the analysis focuses primarily on state-level outcomes, which may mask within-state heterogeneity across sectors, firm sizes, and categories of workers. As such, the findings should be viewed as contextually grounded rather than universally generalizable.

### Future Scope of Study

Future research can extend this study in several directions to enhance generalizability and theoretical depth. Longitudinal research designs with extended time horizons would help capture the dynamic and long-term effects of labour law reforms and AI-enabled governance systems on workforce outcomes. Cross-cultural and cross-national comparative studies could assess the applicability of the findings across different institutional, regulatory, and labour market contexts. Additionally, incorporating firm-level and employee-level data would enable examination of micro-level outcomes such as job satisfaction, work engagement, job insecurity, stress, and well-being. Mixed-method approaches could further enrich understanding of implementation processes and behavioral responses.

## CONCLUSION

This study highlights the dualistic nature of algorithmic and intelligent project management platforms. While these systems enhance managerial self-efficacy and organizational efficiency, they also risk amplifying employee burnout if implemented without human oversight. The results underscore that algorithmic intelligence should not replace managerial judgment but rather augment it.

In essence, sustainable digital leadership arises when human insight and algorithmic precision coexist in balance. By integrating social cognitive and JD-R perspectives, this research advances understanding of how technology reshapes leadership efficacy and well-being in the modern workplace. The findings call for continued exploration of how organizations can design AI-assisted management systems that empower people rather than constrain them.

The study also advances theory by extending Social Cognitive Theory and the Job Demands Resources model to AI-enabled work systems. By demonstrating the dual role of AI as both a job resource and a job demand, the findings highlight the importance of institutional and governance contexts in determining whether AI enhances motivation and performance or intensifies work strain.

While the findings offer robust evidence within the Indian context, their broader applicability depends on institutional, cultural, and regulatory conditions. Future research adopting longitudinal, cross-cultural, and micro-level designs will be essential to deepen understanding of how labour reforms and AI-enabled systems shape workforce outcomes across diverse settings.

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