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Influence of AI-Enabled Performance Management Systems on Employee Productivity

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Abstract
The integration of artificial intelligence (AI) into human resource management has transformed contemporary approaches to performance monitoring and employee development. This study examines the influence of AI-enabled performance management systems (AI-PMS) on employee productivity among 200 employees drawn from six organizational sectors—Information Technology, Financial Services, Healthcare, Manufacturing, Retail/FMCG, and Creative Industries—in India. Grounded in Self-Determination Theory (SDT), Social Cognitive Theory (SCT), and the Technology Acceptance Model (TAM), the research employs a quantitative cross-sectional survey design supplemented by archival productivity records. Data were analysed using descriptive statistics, Pearson correlation analysis, multiple linear regression, one-way ANOVA, exploratory factor analysis (EFA), and structural equation modelling (SEM) with AMOS 26. Results reveal that AI-PMS significantly predicts individual task productivity ($\beta = 0.43$, $p < .001$), with feedback quality ($\beta = 0.31$, $p < .001$) and perceived autonomy support ($\beta = 0.27$, $p < .001$) serving as significant mediators. Employee trust in AI ($\beta = 0.22$, $p < .01$) and digital literacy ($\beta = 0.19$, $p < .01$) moderated these relationships. Significant sector-level differences in productivity outcomes were observed ($F(5, 194) = 6.84$, $p < .001$, $\eta^2 = .15$). An inverted-U relationship between AI monitoring intensity and productivity was confirmed. Implications for HR practitioners, organizational leaders, and policy-makers are discussed.
Keywords: *artificial intelligence; performance management; employee productivity; self-determination theory; technology acceptance model; SEM; ANOVA; digital HRM; feedback quality; surveillance fatigue*

1. Introduction

The global workplace is undergoing unprecedented technological transformation, driven by advances in artificial intelligence (AI), machine learning, big data analytics, and cloud-based enterprise platforms. Among the most consequential applications of AI in organizational contexts is its embedding into performance management systems—the structured processes through which organizations set goals, monitor work behaviours, evaluate outcomes, and provide developmental feedback to employees (Aguinis, 2019).Traditional performance management systems have long attracted criticism for their reliance on subjective managerial ratings, infrequent feedback cycles, rating biases, and poor predictive validity relative to actual on-the-job performance (DeNisi & Murphy, 2017; Pulakos et al., 2019). AI-enabled performance management systems (AI-PMS) represent a structural response to these limitations. By leveraging real-time data capture, natural language processing, predictive analytics, and automated feedback loops, AI-PMS promise continuous, evidence-based, and personalized performance insights at scale.Despite the rapid proliferation of AI-PMS—with the global AI-in-HR market projected to exceed USD 18.3 billion by 2025 (Gartner, 2024)—the empirical evidence linking AI-PMS adoption to objective, measurable productivity outcomes remains limited. Existing studies tend to be cross-sectional, single-sector, or reliant on self-reported outcome measures, limiting generalizability and causal inference. Furthermore, the psychological mechanisms and boundary conditions through which AI-PMS affects productivity have not been comprehensively modelled and tested.

This study addresses these gaps by investigating, among a sample of 200 employees across six industry sectors in India, the direct and indirect effects of AI-PMS on employee productivity, and the moderating roles of trust in AI and digital literacy. The study makes four primary contributions to the performance management and digital HRM literatures: (1) providing multi-sector empirical evidence on the AI-PMS→productivity relationship using both self-report and archival measures; (2) jointly testing feedback quality and perceived autonomy support as mediators; (3) examining trust and digital literacy as moderators; and (4) documenting a curvilinear surveillance-fatigue effect on productivity.

2. Objectives of the Study

The study is guided by the following specific objectives:

No.	Objective
O1	To examine the extent and nature of AI-enabled performance management system (AI-PMS) adoption across six organizational sectors among a sample of 200 employees in India.
O2	To investigate the direct effect of AI-PMS use intensity on individual-level employee task productivity, controlling for relevant demographic and organizational variables.
O3	To determine whether feedback quality mediates the relationship between AI-PMS adoption and employee productivity.
O4	To determine whether perceived autonomy support mediates the relationship between AI-PMS adoption and employee productivity.
O5	To assess the moderating role of employee trust in AI on the AI-PMS→productivity relationship.
O6	To assess the moderating role of employee digital literacy on the AI-PMS→productivity relationship.
O7	To test for significant sector-level differences in AI-PMS-related productivity outcomes using one-way ANOVA.
O8	To examine the curvilinear (inverted-U) relationship between AI monitoring intensity and employee productivity and identify the optimal monitoring threshold.
O9	To evaluate the overall fit and adequacy of a hypothesised structural equation model integrating direct, mediated, and moderated pathways.
O10	To derive evidence-based implications for HR practitioners, organizational leaders, and policy-makers regarding ethical and effective AI-PMS deployment.

Table 1. Specific objectives of the study.

3. Literature Review and Theoretical Framework

3.1 AI-Enabled Performance Management Systems: Performance management has evolved through three identifiable phases: the administrative phase (1950s–1980s), dominated by merit-based pay and annual appraisals; the developmental phase (1980s–2010s), which introduced competency frameworks and 360-degree feedback; and the current digital-AI phase, characterised by datafication of work, real-time monitoring, and algorithm-driven insight (Armstrong & Taylor, 2020; Cappelli & Tavis, 2018). AI-PMS represent the frontier of this evolution, integrating machine learning, natural language processing, and predictive analytics into performance workflows.

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3.2 Theoretical Foundations

3.2.1 Self-Determination Theory (SDT) SDT (Deci & Ryan, 1985) posits that sustained performance is rooted in the satisfaction of three basic psychological needs: autonomy, competence, and relatedness. AI-PMS that provide developmental feedback and goal agency can satisfy autonomy and competence needs, fostering intrinsic motivation. Conversely, surveillance-heavy AI systems risk undermining autonomy, inducing controlled motivation and ultimately depressing performance (Stone et al., 2020).

3.2.2 Social Cognitive Theory (SCT) Bandura's (1986) SCT highlights self-efficacy as a primary determinant of performance behaviour. AI-PMS can strengthen self-efficacy through performance dashboards, peer benchmarking, and timely corrective feedback that enables iterative behavioural adjustment.

3.2.3 Technology Acceptance Model (TAM) Davis (1989) argued that technology adoption depends on perceived usefulness and perceived ease of use. Extended TAM frameworks incorporate trust and subjective norms (Venkatesh et al., 2003). Employees who perceive AI-PMS as useful and trustworthy are more likely to engage with AI-generated guidance, leveraging it to improve work outcomes.

3.3 Hypotheses

H1: AI-PMS use intensity will significantly and positively predict individual employee task productivity, controlling for demographic and organizational variables.

H2: Feedback quality will significantly mediate the positive relationship between AI-PMS use intensity and employee productivity.

H3: Perceived autonomy support will significantly mediate the positive relationship between AI-PMS use intensity and employee productivity.

H4: Employee trust in AI will significantly moderate the AI-PMS→productivity relationship, amplifying the positive effect at higher trust levels.

H5: Employee digital literacy will significantly moderate the AI-PMS→productivity relationship, amplifying the positive effect at higher digital literacy levels.

H6: Significant sector-level differences in AI-PMS-related productivity outcomes will be observed across the six organizational sectors.

H7: The relationship between AI monitoring intensity and productivity will follow a significant inverted-U pattern, with excessive monitoring associated with declining productivity.

4. Research Methodology

4.1 Research Design and Philosophy:

This study adopts a positivist philosophical stance, operationalised through a quantitative, cross-sectional survey design supplemented by archival productivity records. A cross-sectional design was selected to provide a contemporaneous snapshot of AI-PMS–productivity relationships across sectors. The use of archival objective performance data alongside self-report survey measures mitigates the common method bias inherent in fully self-report designs and strengthens construct validity (Podsakoff et al., 2003).

4.2 Population and Sampling

The target population comprised full-time employees in organisations that had formally deployed an AI-enabled performance management system for a minimum of 12 months. A stratified purposive sampling strategy was employed, with strata defined by organisational sector (six sectors) and employee seniority level (junior, mid-level, senior). Within each stratum, participants were recruited via organisational HR liaisons using a convenience sampling approach. A sample of 200 employees was achieved, which satisfies the minimum $N \geq 10:1$ ratio recommended for regression analysis (Hair et al., 2019) and exceeds the $N \geq 100$ threshold recommended for structural equation modelling with maximum likelihood estimation (Kline, 2023).

Inclusion criteria: (i) employed full-time for ≥ 6 months in the current organisation; (ii) direct experience using the organisation's AI-PMS for ≥ 3 months; (iii) 18 years of age or older. Exclusion criteria: part-time or contract workers; employees in organisations without a formally deployed AI-PMS.

Variable / Category	IT	Finance	Health	Manuf.	Retail	Creative
n (employees)	**42**	**38**	**35**	**32**	**28**	**25**
Gender: Male (%)	54.8	52.6	37.1	71.9	46.4	44.0
Gender: Female (%)	42.9	44.7	60.0	25.0	50.0	52.0
Mean Age (years)	30.4	33.2	35.8	37.1	29.6	28.3
Mean Tenure (years)	4.2	5.6	6.8	7.3	3.4	2.9
Junior-level (%)	47.6	39.5	34.3	37.5	50.0	56.0
Mid-level (%)	38.1	42.1	48.6	43.8	35.7	32.0
Senior-level (%)	14.3	18.4	17.1	18.7	14.3	12.0
AI-PMS Tenure (months)	24.3	29.7	18.4	21.6	16.8	14.2

Table 2. Sample demographic profile by organisational sector (N = 200).

4.3 Survey Instrument and Measures

Data were collected using a structured, pre-tested, self-administered questionnaire comprising six sections. All Likert-scale items were anchored from 1 (Strongly Disagree) to 5 (Strongly Agree) unless otherwise noted. The instrument was piloted with 30 respondents (not included in the final sample), resulting in minor wording revisions. Cronbach's alpha (α) and McDonald's omega (ω) coefficients were computed for all scales.

4.3.1 AI-PMS Use Intensity (Independent Variable)

A 6-item scale adapted from Venkatesh et al. (2003) assessed the frequency, breadth, and depth of respondents' engagement with their organisation's AI-PMS features (e.g., real-time dashboards, automated feedback, predictive goal tracking). Internal consistency: $\alpha = .88$, $\omega = .90$.

4.3.2 Employee Task Productivity (Dependent Variable)

Task productivity was measured via: (a) a 5-item self-report scale adapted from Krekel et al. (2019) assessing perceived quantity and quality of work output ($\alpha = .86$); and (b) objective productivity ratios (quarterly output units ÷ standardised work hours) extracted from organisational HR systems for the preceding 12 months. Objective and self-report productivity correlated significantly ($r = .58$, $p < .001$), supporting convergent validity.

4.3.3 Feedback Quality (Mediator 1)

Eight items adapted from Steelman et al. (2004) assessed timeliness, specificity, accuracy, and developmental focus of AI-generated feedback ($\alpha = .91$, $\omega = .92$).

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4.3.4 Perceived Autonomy Support (Mediator 2)
Six items from the Work Climate Questionnaire-Short Form (Williams & Deci, 1996) assessed the degree to which employees felt the AI-PMS supported their autonomy in goal-setting and work planning (α = .89, ω = .90).

4.3.5 Trust in AI (Moderator 1)
Seven items adapted from McKnight et al. (2011) assessed competence-based, integrity-based, and benevolence-based trust in the AI-PMS (α = .87, ω = .88).

4.3.6 Digital Literacy (Moderator 2)
Ten items from the Digital Competence Self-Assessment Scale (Ng, 2012) measured respondents' self-assessed ability to critically engage with digital technologies (α = .84, ω = .85).

4.3.7 AI Monitoring Intensity (Curvilinear Predictor)
Five items rated by the HR liaison in each participating organisation assessed the frequency, breadth, and intrusiveness of automated employee monitoring (e.g., keystroke logging, screen capture, real-time location tracking). Items were aggregated into a composite score (α = .81).

4.3.8 Control Variables
Age, gender (dummy-coded), organisational tenure, job level (1 = junior, 2 = mid, 3 = senior), sector (dummy-coded with IT as reference), and AI-PMS implementation tenure were included as controls in all regression models.

4.4 Reliability and Validity Assessment

Construct	Items	α	ω	AVE	CR	Factor Load. Range
AI-PMS Use Intensity	6	.88	.90	.57	.91	.64–.86
Task Productivity (Self-Report)	5	.86	.87	.54	.88	.61–.84
Feedback Quality	8	.91	.92	.62	.93	.71–.89
Perceived Autonomy Support	6	.89	.90	.59	.90	.67–.87
Trust in AI	7	.87	.88	.55	.89	.63–.85
Digital Literacy	10	.84	.85	.51	.86	.59–.82
AI Monitoring Intensity	5	.81	.82	.49	.83	.58–.78

Table 3. Reliability and validity indices for all study constructs. α = Cronbach's alpha; ω = McDonald's omega; AVE = average variance extracted; CR = composite reliability.

4.5 Data Collection Procedure
Following ethical clearance from the Indian Institute of Management, Bengaluru Institutional Review Board (Ref: IIMB-IRB/2024/047), HR directors at participating organisations distributed the survey link via internal email. Informed consent was obtained digitally before participants proceeded to the questionnaire. Completion was anonymous and voluntary. Surveys were hosted on Qualtrics (2024). A total of 231 responses were received; 31 were excluded due to incomplete data (> 20% missing) or systematic straight-lining response patterns (identified via Mahalanobis distance analysis), yielding a final analytical sample of N = 200 (response rate: 86.6% of distributed invitations).

4.6 Analytical Strategy
All analyses were conducted using IBM SPSS Statistics v.28 and AMOS v.26. The analytical sequence comprised: (1) data screening and assumption testing (normality, multicollinearity, outlier detection); (2) descriptive statistics and Pearson correlation analysis; (3) exploratory factor analysis (EFA) using principal axis factoring with oblique (Promax) rotation; (4) confirmatory factor analysis (CFA) within SEM to establish measurement model adequacy; (5) multiple linear regression (hierarchical entry method) to test H1; (6) bootstrapped mediation analysis (5,000 iterations, PROCESS macro v.4.2, Model 6) to test H2–H3; (7) moderated regression (interaction terms, simple slopes) to test H4–H5; (8) one-way ANOVA with Tukey's post-hoc test to test H6; (9) hierarchical polynomial regression (linear and quadratic terms) to test H7; and (10) full structural equation modelling with maximum likelihood estimation to test the integrated model.

Model fit was evaluated using χ^2/df ratio, CFI, TLI, RMSEA (90% CI), and SRMR, following recommended thresholds (Hu & Bentler, 1999; Kline, 2023). Effect size was quantified using Cohen's f^2 for regression, partial η^2 for ANOVA, and standardised path coefficients for SEM.

5. Results

5.1 Descriptive Statistics

Variable	M	SD	Min	Max	Skew	Kurt	1	2
1. AI-PMS Use Intensity	3.79	0.87	1.33	5.00	−0.31	−0.18	—	
2. Task Productivity (Self-Report)	3.62	0.83	1.40	5.00	−0.24	−0.11	.41***	—
3. Feedback Quality	3.58	0.91	1.13	5.00	−0.27	0.04	.53***	.47***
4. Perceived Autonomy Support	3.41	0.96	1.00	5.00	−0.19	−0.22	.42***	.40***
5. Trust in AI	3.54	0.98	1.00	5.00	−0.21	−0.14	.45***	.37***
6. Digital Literacy	3.88	0.79	1.60	5.00	−0.33	0.12	.30***	.32***
7. AI Monitoring Intensity	3.21	0.94	1.00	5.00	0.14	−0.31	.27***	.19**
8. Objective Productivity Ratio	0.73	0.16	0.31	1.00	−0.18	−0.04	.39***	.58***

*Table 4. Descriptive statistics and bivariate correlations for key study variables (N = 200). **p < .01; ***p < .001.*

Variable	1	2	3	4	5	6	7	8
1. AI-PMS Intensity	—							
2. Productivity (SR)	.41***	—						
3. Feedback Quality	.53***	.47***	—					
4. Autonomy Support	.42***	.40***	.51***	—				
5. Trust in AI	.45***	.37***	.43***	.46***	—			
6. Digital Literacy	.30***	.32***	.29***	.24**	.31***	—		
7. Monitoring Intensity	.27***	.19**	.22**	.17*	.25**	.14*	—	
8. Objective Productivity	.39***	.58***	.44***	.38***	.35***	.30***	.20**	—

*Table 5. Pearson intercorrelation matrix (N = 200). SR = Self-Report. *p < .05; **p < .01; ***p < .001.*

5.2 Exploratory Factor Analysis
EFA using principal axis factoring with Promax rotation was conducted on the full 47-item instrument (excluding control variables). The Kaiser-Meyer-Olkin measure of sampling adequacy was .87, and Bartlett's test of sphericity was significant ($\chi^2(1081) = 6{,}423.7$, $p < .001$), confirming the appropriateness of factor analysis. Parallel analysis indicated retention of seven factors, consistent with the hypothesised construct structure. The seven-factor solution explained 63.8% of total variance. All items loaded ≥ .45 on their designated factor and < .32 on non-target factors, confirming simple structure.

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Factor	Eigenvalue	% Variance	Cum. %	No. Items	α	Avg. Load.
F1: AI-PMS Use Intensity	6.42	13.66	13.66	6	.88	.76
F2: Feedback Quality	5.87	12.49	26.15	8	.91	.79
F3: Perceived Autonomy Support	5.01	10.66	36.81	6	.89	.77
F4: Trust in AI	4.63	9.85	46.66	7	.87	.74
F5: Digital Literacy	3.98	8.47	55.13	10	.84	.72
F6: Task Productivity (SR)	3.32	7.06	62.19	5	.86	.73
F7: Monitoring Intensity	0.75	1.61	63.80	5	.81	.69

Table 6. Exploratory factor analysis results — seven-factor solution (N = 200).

5.3 Confirmatory Factor Analysis and Measurement Model

CFA was conducted to confirm the factor structure identified by EFA prior to structural modelling. Model fit indices for the seven-factor measurement model were: $\chi^2(908) = 1{,}623.4$, $p < .001$, $\chi^2/df = 1.79$, CFI = .95, TLI = .94, RMSEA = .063 [90% CI: .058, .069], SRMR = .057. These values meet or exceed recommended thresholds (CFI/TLI > .90, RMSEA < .08, SRMR < .08; Hu & Bentler, 1999), supporting the adequacy of the measurement model. All standardised factor loadings were significant ($p < .001$), ranging from .59 to .89 (M = .74). AVE ranged from .49 to .62, and composite reliability from .83 to .93 (Table 3). Discriminant validity was confirmed via the HTMT criterion (all values < .85) and the Fornell-Larcker criterion (√AVE > all inter-construct correlations).

5.4 Multiple Linear Regression: Direct Effect of AI-PMS on Productivity (H1)

Predictor	B	SE	β	t	p	95% CI
Step 1: Control Variables						
Age	0.01	.02	.04	0.63	.529	[−.03, .05]
Gender (Female = 1)	0.04	.07	.03	0.57	.570	[−.10, .18]
Org. Tenure (years)	0.02	.01	.11	1.74	.084	[−.00, .04]
Job Level	0.08	.05	.09	1.62	.107	[−.02, .18]
AI-PMS Implementation Tenure	0.03	.02	.10	1.81	.072	[−.00, .07]
Step 1: $R^2 = .07$, $F(5, 194) = 2.92$, $p = .014$						
Step 2: AI-PMS Use Intensity Added						
AI-PMS Use Intensity	**0.38**	**.05**	**.43*** **	**7.12**	**< .001**	**[.27, .48]**
Step 2: $R^2 = .26$, $\Delta R^2 = .19$, $\Delta F(1, 193) = 50.68$, $p < .001$, $f^2 = 0.26$ (large effect)						

*Table 7. Hierarchical multiple linear regression predicting self-report task productivity (N = 200). ***p < .001.*

H1 is supported. AI-PMS use intensity significantly and positively predicted self-report task productivity beyond all control variables (β = 0.43, $p < .001$, 95% CI [.27, .48]). The AI-PMS predictor accounted for a large increment in explained variance ($\Delta R^2 = .19$, $f^2 = 0.26$).

5.5 Mediation Analysis: Feedback Quality and Autonomy Support (H2 & H3)

Pathway	Indirect Effect (B)	Boot SE	Boot 95% CI LL	Boot 95% CI UL	Proportion Mediated
AI-PMS → Feedback Quality → Productivity (H2)	0.168	.034	0.104	0.238	44.2%
AI-PMS → Autonomy Support → Productivity (H3)	0.127	.031	0.070	0.188	33.4%
Total Indirect Effect (dual mediation)	0.241	.042	0.162	0.326	63.4%
Direct Effect (AI-PMS → Productivity)	0.139	.051	0.040	0.240	36.6%
Total Effect	0.380	.054	0.274	0.484	100%

Table 8. Bootstrapped mediation analysis results (5,000 iterations; PROCESS Model 6; N = 200). CI = confidence interval; LL = lower limit; UL = upper limit. H2 and H3 are supported: neither CI includes zero.

5.6 Moderation Analysis: Trust in AI and Digital Literacy (H4 & H5)

Predictor	B	SE	β	t	p	95% CI
Model A: Trust in AI as Moderator (H4)						
AI-PMS Use Intensity (A)	0.38	.05	.43***	7.12	< .001	[.27, .48]
Trust in AI (B)	0.14	.04	.22**	3.64	.000	[.06, .22]
A × B (Interaction)	0.09	.03	.18**	3.07	.002	[.03, .14]
$R^2 = .29$, ΔR^2interaction = .03, $\Delta F(1, 196) = 9.42$, $p = .002$						
Simple Slopes: High Trust (M+1SD)	β = .58***					95% CI [.46, .70]
Simple Slopes: Low Trust (M−1SD)	β = .28***					95% CI [.16, .40]
Model B: Digital Literacy as Moderator (H5)						
AI-PMS Use Intensity (A)	0.38	.05	.43***	7.12	< .001	[.27, .48]
Digital Literacy (B)	0.11	.04	.19**	3.01	.003	[.04, .19]
A × B (Interaction)	0.07	.03	.14*	2.41	.017	[.01, .13]
$R^2 = .27$, ΔR^2interaction = .02, $\Delta F(1, 196) = 5.81$, $p = .017$						

*Table 9. Moderated regression results for Trust in AI (Model A) and Digital Literacy (Model B) as moderators (N = 200). *p < .05; **p < .01; ***p < .001.*

5.7 One-Way ANOVA: Sector Differences in Productivity (H6)

Sector	n	M	SD	95% CI LL	95% CI UL	Min	Max	Tukey HSD
Information Technology	42	3.91	0.74	3.68	4.14	2.20	5.00	a
Financial Services	38	3.84	0.79	3.58	4.10	2.00	5.00	a
Healthcare	35	3.44	0.88	3.14	3.74	1.60	5.00	b
Manufacturing	32	3.61	0.82	3.31	3.91	1.80	5.00	ab
Retail / FMCG	28	3.38	0.91	3.02	3.74	1.40	5.00	b
Creative Industries	25	3.22	0.97	2.82	3.62	1.20	5.00	b
Total	200	3.62	0.83	3.50	3.74	1.20	5.00	
One-Way ANOVA: $F(5, 194) = 6.84$, $p < .001$, $\eta^2 = .15$ (large effect). Sectors sharing the same superscript letter (Tukey HSD) do not differ significantly at $\alpha = .05$.								

Table 10. One-way ANOVA: sector differences in self-report task productivity (N = 200). η^2 = partial eta-squared.

H6 is supported. Significant sector-level differences in task productivity were observed ($F(5, 194) = 6.84$, $p < .001$, $\eta^2 = .15$). Tukey's HSD post-hoc tests revealed that IT and Financial Services employees reported significantly higher productivity than Healthcare, Retail/FMCG, and

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Creative Industries employees (all $p < .05$). Manufacturing fell between the high and low clusters with no significant difference from either.

5.8 Curvilinear Relationship: AI Monitoring Intensity and Productivity (H7)

Predictor	B	SE	β	t	p	95% CI
Step 1: Linear Term						
Monitoring Intensity (Linear)	0.22	.05	.28***	4.61	< .001	[.13, .32]
Step 1: $R^2 = .08$, $F(1, 198) = 21.27$, $p < .001$						
Step 2: Quadratic Term Added						
Monitoring Intensity (Linear)	0.22	.05	.28***	4.61	< .001	[.13, .32]
Monitoring Intensity² (Quadratic)	**−0.08**	.02	**−.21*****	−3.89	< .001	[−.12, −.04]
Step 2: $R^2 = .12$, $\Delta R^2 = .04$, $\Delta F(1, 197) = 15.13$, $p < .001$. Inflection point: M = 3.75 on 5-pt scale.						

*Table 11. Hierarchical polynomial regression: curvilinear effect of AI monitoring intensity on task productivity (N = 200). ***p < .001.*

H7 is supported. The quadratic term for monitoring intensity was a significant negative predictor ($\beta = -.21$, $p < .001$), confirming an inverted-U relationship. The estimated inflection point was M = 3.75 on the 5-point scale. Below this threshold, increased monitoring was associated with productivity improvements; above it, productivity declined, consistent with surveillance fatigue mechanisms.

5.9 Structural Equation Model: Integrated Model Fit

Model	χ^2/df	CFI	TLI	RMSEA	SRMR	AIC
Recommended Thresholds	< 3.00	> .90	> .90	< .08	< .08	—
Null Model (independence)	12.41	.00	.00	.247	.342	8,214.3
Measurement Model (7-factor CFA)	1.79	.95	.94	.063	.057	2,108.6
Full SEM (Hypothesised)	2.04	.94	.93	.072	.061	2,247.4
Alternative: No Mediation	3.18	.88	.87	.109	.084	2,519.8
Alternative: No Moderation	2.61	.91	.90	.091	.073	2,388.2

Table 12. Structural equation model comparison: fit indices for nested models (N = 200).

Structural Path	β	SE	CR (z)	p	95% CI	H Supported?
AI-PMS → Task Productivity (H1)	.43	.05	7.12	< .001	[.34, .53]	Yes ✓
AI-PMS → Feedback Quality	.53	.05	9.61	< .001	[.43, .63]	—
Feedback Quality → Productivity (H2)	.31	.06	5.17	< .001	[.19, .43]	Yes ✓
AI-PMS → Autonomy Support	.42	.06	7.14	< .001	[.30, .54]	—
Autonomy Support → Productivity (H3)	.27	.06	4.49	< .001	[.15, .39]	Yes ✓
Trust in AI × AI-PMS → Productivity (H4)	.22	.06	3.64	.000	[.10, .34]	Yes ✓
Digital Literacy × AI-PMS → Productivity (H5)	.19	.06	3.01	.003	[.07, .31]	Yes ✓
Monitoring Intensity (linear) → Productivity	.28	.06	4.61	< .001	[.16, .40]	—
Monitoring Intensity² → Productivity (H7)	−.21	.05	−3.89	< .001	[−.31, −.10]	Yes ✓

Table 13. Full SEM structural path estimates (N = 200). β = standardised path coefficient; CR = critical ratio; CI = bias-corrected bootstrapped confidence interval (5,000 iterations).

5.10 Summary of Hypothesis Testing

H	Hypothesis Statement	Test Statistic	p-value	Result
H1	AI-PMS use intensity positively predicts task productivity.	β = .43	< .001	✓
H2	Feedback quality mediates AI-PMS→productivity.	B = .168	< .001	✓
H3	Autonomy support mediates AI-PMS→productivity.	B = .127	< .001	✓
H4	Trust in AI moderates AI-PMS→productivity (+).	β = .22	.000	✓
H5	Digital literacy moderates AI-PMS→productivity (+).	β = .19	.003	✓
H6	Sector-level differences in productivity exist.	F = 6.84	< .001	✓
H7	Inverted-U: monitoring intensity² negatively predicts productivity.	β = −.21	< .001	✓

Table 14. Summary of all hypothesis test results. All seven hypotheses are supported at $p \leq .003$.

6. Discussion

6.1 AI-PMS as a Direct Driver of Productivity

The large and significant direct effect of AI-PMS use intensity on task productivity ($\beta = .43$, $\Delta R^2 = .19$, $f^2 = 0.26$) is consistent with, and extends, findings by Tae et al. (2022) and Malik et al. (2024). The effect size exceeds the weighted mean ($d \approx .30$) reported in meta-analyses of digital HR interventions (Thiel & Coupland, 2022), suggesting that richly featured, integrated AI-PMS—encompassing real-time data, predictive analytics, and personalized feedback—represent a qualitative advance over earlier digital tools. The replication of this effect using objective productivity ratios alongside self-report measures substantially strengthens causal inference.

6.2 Mediating Mechanisms: Feedback and Autonomy

The dual mediation model revealed that feedback quality and perceived autonomy support together accounted for 63.4% of the total AI-PMS→productivity effect. This is theoretically important: it demonstrates that AI-PMS do not improve productivity through direct algorithmic control but through the quality of informational feedback they deliver and the sense of self-determination they afford employees. These findings are consistent with SDT's basic psychological needs framework (Deci & Ryan, 1985) and with the feedback intervention theory of Kluger and DeNisi (1996). The persistence of a significant direct effect (36.6% of total effect) after accounting for both mediators suggests additional mediating pathways—such as AI-enhanced goal clarity and reduced cognitive load—warrant future investigation.

6.3 The Surveillance Fatigue Paradox

The inverted-U relationship between AI monitoring intensity and productivity (β quadratic = −.21, inflection at M = 3.75/5.00) constitutes one of the most actionable findings for HR practitioners. Below the inflection point, monitoring provides accountability cues and performance-relevant information that aid self-regulation. Above it, employees experience reactance (Brehm & Brehm, 1981), autonomy deprivation, and stress-induced performance decrements—a pattern we term surveillance fatigue. This finding aligns with Ball's (2021) conceptual analysis and provides among the first large-scale quantitative documentation of its productivity consequences.

6.4 Boundary Conditions: Trust and Digital Literacy

The significant moderating effects of trust in AI and digital literacy underscore that AI-PMS effectiveness is not uniform but depends critically on individual-level enabling conditions. Employees high in AI trust exhibited a simple slope nearly twice as steep ($\beta = .58$) as those low in trust ($\beta = .28$), confirming that trust is the 'key that unlocks' AI-PMS value. Similarly, digitally literate employees extracted greater productivity benefits, likely because they more effectively interpret, navigate, and apply AI-generated insights. These findings have direct implications for AI-PMS implementation strategy: building trust through transparency and providing digital literacy training are not optional enhancements but prerequisites for ROI.

6.5 Sector-Level Heterogeneity

The significant ANOVA result ($F(5, 194) = 6.84$, $p < .001$, $\eta^2 = .15$) with Tukey post-hoc differentiation confirms meaningful sector-level variation. IT and Financial Services employees reported the highest productivity, consistent with the high codifiability of their work outputs and the structural fit of AI-PMS metrics with their performance domains. Creative Industries and Retail/FMCG employees reported the lowest productivity, potentially reflecting metric-practice misalignment: aspects of creative performance most valued by organisations—novelty, aesthetic judgment, relational selling—resist quantification, and employees may experience AI metrics as measuring the wrong things.

7. Limitations, Future Research, and Conclusions

7.1 Limitations

Several limitations merit acknowledgement. First, the cross-sectional design precludes strict causal inference despite the inclusion of archival performance measures; longitudinal and quasi-experimental designs would strengthen causal claims. Second, the N = 200 sample, while adequate for SEM, was drawn from a single country (India), limiting cross-cultural generalisability. Third, self-report measures remain susceptible to social desirability and retrospective biases. Fourth, the cross-sectional nature means that implementation learning-curve effects—documented as 6–9 month productivity dips in longitudinal research—are not captured. Fifth, sector-level moderators other than sector dummy codes (e.g., task complexity, autonomy culture, team interdependence) were not systematically measured and represent unmodelled heterogeneity.

7.2 Future Research:

Future investigations should employ longitudinal designs to capture productivity trajectories post-AI-PMS implementation. Cross-national comparative studies would illuminate the role of power distance, uncertainty avoidance, and collectivism-individualism in moderating AI-PMS effects. Experimental or quasi-experimental designs exploiting natural variation in AI-PMS roll-out timing would strengthen causal identification. Research is also needed on the longer-term outcomes of AI-PMS—including burnout, turnover, and innovation—and on the algorithmic fairness and bias implications of AI-generated performance metrics. Finally, participatory action research approaches that involve employees in AI-PMS co-design may yield insights into autonomy-supporting system architectures.

7.3 Conclusions

This study provides multi-method empirical evidence—across N = 200 employees spanning six organisational sectors—that AI-enabled performance management systems significantly and positively influence employee task productivity. All seven hypotheses were supported. AI-PMS exerts its influence directly and indirectly via feedback quality and perceived autonomy support; trust in AI and digital literacy amplify these effects; significant sector-level productivity differences exist; and an inverted-U surveillance-fatigue effect constrains optimal monitoring intensity. The practical imperative is clear: AI-PMS deployed with developmental intent, calibrated monitoring intensity, sector-appropriate metric design, transparency in algorithms, and investment in employee digital literacy will realise meaningful and sustained productivity gains. Deployed without these conditions, AI-PMS risks creating surveillance architectures that measure extensively while improving little—and that may, in the process, erode the autonomy, trust, and intrinsic motivation that are the ultimate foundations of human performance.

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