“AI and performance management efficiency: A quantitative survey”

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AI AND PERFORMANCE MANAGEMENT EFFICIENCY: A QUANTITATIVE SURVEY

Abstract

This study examines how artificial intelligence (AI) is associated with perceived performance management efficiency of organizations in the United Kingdom. Drawing on the technology acceptance model (TAM), the study tests a revised partial least squares structural equation modeling (PLS-SEM) model in which AI implementation level and AI sophistication predict perceived usefulness, AI training for HR teams predicts perceived ease of use, perceived ease of use predicts perceived usefulness, and perceived usefulness, together with AI utilization maturity, predicts performance management efficiency. Data were collected from 320 decision-makers in the United Kingdom using AI in performance management. The results support all six hypotheses: AI implementation level (beta = 0.188, $p < .001$), AI sophistication (beta = 0.222, $p < .001$), AI training for HR teams (beta = 0.256, p < .001), perceived ease of use (beta = 0.336, $p < .001$), perceived usefulness (beta = 0.324, $p < .001$), and AI utilization maturity (beta = 0.405, $p < .001$) were positively associated with their respective endogenous constructs. The model explained 36.0% of the variance in perceived performance management efficiency. The findings contribute to research on AI-enabled HR analytics by showing how organizational AI capabilities and TAM perceptions jointly predict perceived improvements in performance management.

Keywords technology acceptance model, AI utilization maturity, HR analytics, perceived usefulness, perceived ease of use, PLS-SEM, United Kingdom, organizations

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INTRODUCTION

Artificial intelligence (AI) is increasingly reshaping work, management, and organizational decision-making. Recent research on generative AI and digital technologies shows that AI can improve productivity and decision support, while also creating new managerial, ethical, and implementation challenges (Brynjolfsson et al., 2025; Dwivedi et al., 2023; Noy & Zhang, 2023; Raisch & Krakowski, 2021). In human resource management (HRM), AI is now being used to support recruitment, talent management, learning, analytics, performance appraisal, and feedback processes (Budhwar et al., 2022; Gong et al., 2024; Tambe et al., 2019; Vrontis et al., 2021).

Within this broader shift, performance management is a particularly important application area because it combines data-intensive evaluation, feedback, employee development, and managerial decision-making. AI-enabled performance systems may support more timely feedback, predictive insights, and data-based decision support, but their value depends on how employees and decision-makers perceive, understand, and use these systems (Aguinis, 2019; DeNisi & Murphy, 2017; Pan et al., 2025; Pulakos et al., 2015).

However, AI-enabled HRM also raises substantial implementation challenges. Prior research highlights concerns about algorithmic opacity, fairness, privacy, accountability, employee involvement, and

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the risk that algorithmic systems may intensify managerial control rather than improve employee experience (Bennett & Martin, 2026; Kellogg et al., 2020; Lamers et al., 2024; Taslim et al., 2025). These concerns are especially relevant in performance management because appraisal and feedback systems directly affect perceived fairness, employee trust, and organizational justice.

Organizational and human-capability factors also matter. HR professionals and managers need sufficient analytical, technical, and interpretive skills to work effectively with AI-supported systems (Marler & Boudreau, 2016; Radonjić et al., 2024; Thakur et al., 2024). Employees' trust in AI and their responses to AI-generated feedback may also depend on leadership support, perceived transparency, and the extent to which AI is experienced as augmenting rather than replacing human judgment (Raisch & Krakowski, 2021; Wang et al., 2026; Xu et al., 2024).

Performance management remains a central HRM process because it links individual behavior, feedback, development, rewards, and organizational goals. Yet the field has long struggled with dissatisfaction, bias, poor feedback quality, and weak developmental value (Aguinis et al., 2011; DeNisi & Murphy, 2017; Pulakos et al., 2015). This makes AI-enabled performance management a timely research area: AI may support more data-rich, continuous evaluation, but it may also amplify concerns about fairness, surveillance, and acceptance.

Existing research on AI HRM, HR analytics, algorithmic management, and performance appraisal provides important foundations, but the mechanisms linking organizational AI capabilities to perceived performance management efficiency remain underdeveloped (Gong et al., 2024; Jangbahadur et al., 2024; Kim et al., 2024; Marler & Boudreau, 2016; Pan et al., 2025). This study addresses that gap by testing a technology acceptance model (TAM)-aligned PLS-SEM model in which AI implementation, AI sophistication, AI training, and AI utilization maturity are connected to perceived performance management efficiency through perceived usefulness and perceived ease of use.

1. LITERATURE REVIEW

Performance management efficiency (PME) refers here to the perceived extent to which performance management systems support accurate evaluation, bias reduction, process speed, productivity tracking, and decision quality. Performance management is commonly understood as an ongoing process through which organizations define expectations, monitor performance, provide feedback, support development, and align individual contributions with strategic goals (Aguinis, 2019; DeNisi & Murphy, 2017).

The effectiveness of performance management matters because poorly designed appraisal systems can generate dissatisfaction and undermine development, whereas well-designed systems can support learning, goal alignment, and behavior change (Aguinis et al., 2011; Pulakos et al., 2015). Employee experience, relational context, and perceived fairness remain central to the success of appraisal systems, including AI-supported appraisal (Bennett & Martin, 2026; Pan et al., 2025).

The relevance of PME has intensified as organizations move from periodic appraisal toward more continuous, data-enabled, and analytics-supported performance management. HR analytics research argues that data-driven HR systems can improve decision quality when analytics are embedded in organizational capabilities and managerial routines (Marler & Boudreau, 2016; Thakur et al., 2024; Vanhove et al., 2025). AI, therefore, represents not only a technical tool but also a change in how performance information is generated, interpreted, and acted upon.

AI HRM research has expanded rapidly, with reviews showing that AI can support HR decision-making while also creating challenges related to skills, transparency, accountability, ethics, and strategic integration (Budhwar et al., 2022; Gong et al., 2024; Tambe et al., 2019; Vrontis et al., 2021). Studies of AI-enabled HRM also suggest that AI-related capabilities can be associated with engagement, sustainable organizational performance, and more advanced talent-management practices, particularly when human skills and organizational readiness are developed alongside the technology (Jangbahadur et al., 2024; Kim et al., 2024).

A parallel literature on algorithmic management cautions that AI-supported HR systems should not be treated as neutral or purely efficiency-enhancing. Algorithms can reshape managerial control, employee voice, and perceptions of fairness (Kellogg et al., 2020; Lamers et al., 2024). This is especially important for AI-driven performance management because automated feedback and appraisal systems may influence trust, motivation, and perceived justice (Bennett & Martin, 2026; Taslim et al., 2025; Wang et al., 2026).

AI implementation level captures the perceived extent to which AI is embedded in performance-management activities. From an HR analytics and AI HRM perspective, the breadth of AI implementation is important because isolated tools are less likely to generate value than systems integrated into decision routines, workflows, and HR processes (Marler & Boudreau, 2016; Tambe et al., 2019; Vrontis et al., 2021).

AI sophistication captures the perceived technical capability of AI systems, including advanced analytics, real-time feedback, performance prediction, and system learning. This distinction is important because AI systems vary in whether they merely automate existing tasks or augment decision-making through predictive and adaptive capabilities (Raisch & Krakowski, 2021; Vanhove et al., 2025). Highly sophisticated systems may, therefore, be perceived as more useful when they provide timely, interpretable, and actionable performance information.

AI training for HR teams reflects the human-capability side of AI-enabled performance management. Prior research on HR analytics and AI-HRM emphasizes that technological value depends on users' analytical competence, interpretive ability, and confidence in applying AI-supported insights (Budhwar et al., 2022; Marler & Boudreau, 2016; Radonjić et al., 2024; Thakur et al., 2024). Training is, therefore, expected to increase perceived ease of use by reducing uncertainty and improving users' ability to interact with AI tools.

AI utilization maturity captures accumulated experience, increased use over time, employee familiarity, and improved integration. This construct reflects the idea that organizations develop routines and complementary capabilities around digital technologies through repeated use and learning. In AI HRM, maturity is likely to matter because the value of AI systems depends on organizational learning, responsible integration, and the balance between automation and human augmentation (Chowdhury et al., 2024; Kim et al., 2024; Raisch & Krakowski, 2021).

Existing research offers valuable insights into AI-HRM, HR analytics, algorithmic management, and performance appraisal. However, limited quantitative evidence explains how AI implementation level, AI sophistication, AI training for HR teams, AI utilization maturity, perceived usefulness, and perceived ease of use jointly predict perceived performance management efficiency within UK organizations (Gong et al., 2024; Marler & Boudreau, 2016; Pan et al., 2025; Tambe et al., 2019; Vrontis et al., 2021). This study addresses this gap by testing a TAM-aligned PLS-SEM model that links organizational AI capabilities to performance management efficiency via core technology acceptance perceptions.

The theoretical foundation of the study is the technology acceptance model (TAM), which argues that technology acceptance is shaped by perceived usefulness and perceived ease of use (Davis, 1989). TAM has been extended and compared with related acceptance models in later research, including TAM2, the Theory of Planned Behavior, and UTAUT (Ajzen, 1991; Taylor & Todd, 1995; Venkatesh & Davis, 2000; Venkatesh et al., 2003, 2012). In the context of AI-enabled performance management, organizational AI capabilities are expected to influence users' perceptions of usefulness and ease of use, which in turn predict perceived performance management efficiency. AI implementation level and AI sophistication are expected to strengthen perceived usefulness by increasing the visibility, functionality, and practical value of AI-enabled performance management systems. AI-related training is expected to improve perceived ease of use by increasing users' confidence and ability to interact with AI tools. Finally, AI utilization maturity is expected to have a direct positive association with performance management efficiency, as organizations

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with greater AI experience are likely to have more developed routines, greater user familiarity, and better integration of AI into performance management processes.

This study aims to test how organizational AI capabilities and technology-acceptance perceptions jointly predict perceived performance management efficiency among decision-makers in UK organizations. The hypotheses are as follows:

H1: AI implementation level is positively associated with perceived usefulness of AI-enabled performance management systems.

H2: AI sophistication is positively associated with perceived usefulness of AI-enabled performance management systems.

H3: AI training for HR teams is positively associated with perceived ease of use of AI-enabled performance management systems.

H4: Perceived ease of use is positively associated with perceived usefulness of AI-enabled performance management systems.

H5: Perceived usefulness is positively associated with performance management efficiency.

H6: AI utilization maturity is positively associated with performance management efficiency.

2. METHOD

2.1. Population and sampling

The unit of analysis in this study is the individual decision-maker's perception of AI-enabled performance management practice within their organization. Although respondents reported on organizational practices, the data were collected at the individual respondent level from HR managers, IT managers, senior executives, and other relevant organizational decision-makers. Therefore, the findings should be interpreted as perceived organizational-level AI use and perceived performance management efficiency rather than as independently verified firm-level performance outcomes. To reduce ambiguity, the final sample is described as 320 valid respondents from UK organizations using AI in performance management, rather than 320 independent firms, unless one response per firm can be confirmed.

The analysis targeted UK-based organizations that had implemented or were adopting AI in performance management. A stratified sampling strategy was used to support representation across industries, respondent roles, and AI maturity levels. The final sample comprised 320 valid respondents from organizations that use AI in performance management (Table 1).

Table 1. Demographics

Demographics/Attributes	Percentage of Respondents
Industry Sector	
Technology	25%
Finance	20%
Healthcare	15%
Retail	10%
Manufacturing	10%
Other (Hospitality, Education, etc.)	20%
Role in the Firm	
HR Head	50%
IT Head	50%
Duration of AI Utilization	
Less than 1 year	15%
1–3 years	35%
3–5 years	30%
More than 5 years	20%

2.2. Questionnaires

The distribution of the questionnaire took on a multifaceted approach to optimize reach and enhance the response rate:

- Email: A formal e-invitation was sent to the HR and IT heads' official email addresses. The email contained an introduction to the study, its significance, and a link to the questionnaire.
- Post: For firms identified as not very responsive to digital communications or with stringent email firewall rules, a hard copy of the questionnaire, accompanied by a cover letter, was sent by post.
- Google Forms: A user-friendly, popular tool used to design the online version of the ques-

tionnaire. Its link was shared both via email and WhatsApp.

- WhatsApp Links: Recognizing the increasing corporate reliance on instant messaging tools like WhatsApp, we shared the Google Forms link with respondents who had shown preliminary interest in the study via this medium.

- Physical Visits: Personal visits were scheduled with key firms, especially those in the vicinity and those with significant industry influence. During these visits, the questionnaire was distributed in hard copy, and respondents could also complete it digitally on provided tablets.

Selecting HR and IT leaders as major respondent groups was intentional because AI-enabled performance management sits at the intersection of HR practice, analytics capability, and digital systems. HR leaders are positioned to assess appraisal, feedback, and talent management implications, while IT leaders are positioned to assess system integration and technical capabilities. This respondent strategy is consistent with HR analytics and AI HRM research, which emphasize the joint importance of HR expertise, digital capability, and managerial interpretation (Budhwar et al., 2022; Marler & Boudreau, 2016; Radonjić et al., 2024; Tambe et al., 2019).

The survey was distributed to 720 potential respondents. A total of 379 responses were received, of which 28 were removed due to substantial incompleteness, 18 because respondents indicated their organization did not use AI in performance management, and 13 following data-quality screening. The final dataset comprised 320 usable responses, representing a gross response rate of 52.6% and a usable response rate of 44.4%, see Table 2.

Table 2. Survey response and screening summary

Survey stage	Number
Organizations/respondents contacted	720
Responses received	379
Incomplete responses removed	28
Non-AI users screened out	18
Careless/invalid responses removed	13
Final usable responses	320
Gross response rate	52.60%
Usable response rate	44.40%

2.3. Ethical considerations and participant consent

In accordance with national and international research ethics guidelines, this study adhered to strict ethical protocols to protect the rights of the 320 participants. Before completing the survey, all respondents were provided with an informed consent briefing that detailed the study's aim, the voluntary nature of their participation, and their right to withdraw at any stage without penalty. To ensure complete anonymity and confidentiality, no personal identifiers, such as names or specific IP addresses, were collected or stored. All data were encrypted and used solely for academic purposes, ensuring that individual responses could not be traced back to specific organizations or personnel.

2.4. Levene's test and non-response bias assessment

Non-response bias was assessed by comparing responses across key groups using variance and mean-difference tests. This procedure examined whether responses differed materially across response methods and selected organizational characteristics.

Table 3 shows that Levene's F value for the response method suggests no significant difference in the variances of the two groups. The t-test indicates a marginal difference in means between the

Table 3. Non-response bias tests

Comparison	Levene's Test F Value	Levene's Test Sig.	T-Test T Value	T-Test DF	T-Test Sig. (2-Tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference
Response Method: Email vs Post	2.43	0.121	1.67	318	0.096	0.52	0.31	(–0.08, 1.12)
Firm Characteristics: Tech vs Non-Tech	1.98	0.161	2.12	318	0.035	0.47	0.22	(0.04, 0.90)

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two groups, but it is not statistically significant. This implies that the response method (email or post) does not induce a substantial bias in the results. Similarly, while the t-test for firm characteristics (Tech vs. Non-Tech) is significant, Levene's test indicates that the variance is not significant.

2.5. Common method bias (CMB)

Common method bias refers to variance attributable to the measurement method rather than the constructs being measured. Because the study used a questionnaire survey, procedural and statistical checks were applied to reduce and assess common method bias (Podsakoff et al., 2003; Kock, 2015).

Table 4. Harman's single-factor test

Harman's Single Factor Test	Total variance (%)
Unrotated Factor Solution	24.8%
First Factor Eigenvalue	3.51

Harman's single-factor test was used as an initial diagnostic (Table 4). If a single factor emerges or one factor accounts for most of the covariance among the measures, common method bias may be present (Podsakoff et al., 2003). In this study, the first factor explained 24.8% of the variance, below the commonly used 50% threshold. Thus, the initial test did not indicate a serious common method bias problem.

Common method bias was also assessed using a full collinearity approach. Each latent construct was regressed on the remaining latent constructs, and the resulting VIF values (Table 5) were inspected against the conservative 3.3 threshold recommended in PLS-SEM applications (Kock, 2015). All full collinearity VIF values were below 3.3, suggesting that common method bias was unlikely to distort the estimated relationships materially. Together, the procedural remedies, Harman's single-factor result, and full collinearity diagnostics indicate that common method bias was not a major threat in this study.

Table 5. Full collinearity assessment

Construct	R^2 when regressed on all other constructs	Full collinearity VIF	Assessment
AIL	0.251	1.336	Pass
AIS	0.358	1.558	Pass
AIT	0.344	1.526	Pass
AIUM	0.306	1.441	Pass
PU	0.369	1.584	Pass
PEOU	0.228	1.295	Pass
PME	0.496	1.984	Pass

Note: AIL = AI Implementation Level; AIS = AI Sophistication; AIT = AI Training for HR Teams; AIUM = AI Utilization Maturity; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

2.6. Construct measurement and data analysis

The complete questionnaire items are reported in Appendix A (Table A1), with evidence of content validity (Table A2), the measurement model specification (Table A3), and indicator outer loadings (Table A4). The questionnaire items were developed from prior literature on TAM, AI adoption, HR analytics, and performance management, and were adapted to the context of AI-enabled performance management. Perceived usefulness and perceived ease of use were adapted from TAM-based measurement logic (Davis, 1989; Venkatesh & Davis, 2000). Items for AI implementation, AI sophistication, AI training, and AI utilization maturity were informed by the AI HRM, HR analytics, and algorithmic management literature (Budhwar et al., 2022; Gong et al., 2024; Marler & Boudreau, 2016; Tambe et al., 2019; Vrontis et al., 2021). PME items were informed by performance management and appraisal literature (Aguinis, 2019; DeNisi & Murphy, 2017; Pulakos et al., 2015). All substantive items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The revised model specified all latent constructs as reflective Mode A constructs. AI utilization maturity replaced the earlier duration of AI utilization label because the items capture organizational experience, accumulated familiarity, increased use, and improved integration, rather than simple chronological duration.

Before analysis, the dataset was screened for eligibility, completeness, and response quality. Respondents who indicated that their organization did not use AI in performance management were excluded. Substantially incomplete questionnaires were removed, and the remaining responses were checked for straight-lining, duplicate entries, and unusual response patterns. Outlier checks were conducted using standardized scores and multivariate response diagnostics. After data screening, 320 valid responses (Table 6) were retained for the PLS-SEM analysis. These procedures helped ensure that the final dataset was suitable for measurement and structural model assessment.

Table 6. Data screening and final sample

Check	Procedure	Result
Screening	Retained only respondents from organizations using AI in performance management	18 removed
Missing data	Checked item-level missingness and removed substantially incomplete questionnaires	28 removed
Straight-lining	Checked identical answers across all Likert-scale items	7 removed
Duplicate responses	Checked timestamps, organization identifiers, and response patterns where available	3 removed
Outliers	Checked standardized scores and multivariate response patterns	3 removed
Common method bias	Harman's single-factor test and full collinearity VIF	No major concern
Final sample	Valid responses retained for analysis	320

PLS-SEM was used because the study focuses on prediction, theory extension, and the simultaneous assessment of measurement and structural relationships among latent constructs (Chin, 1998; Hair et al., 2019; Hair et al., 2022; Henseler et al., 2016). The model was assessed in two stages: first, the measurement model was evaluated using outer loadings, indicator reliability, Cronbach's alpha, rho_A, composite reliability, AVE, and HTMT; second, the structural model was evaluated using inner VIF values, bootstrapped path coefficients, R2, f2, Q2 predict, and model fit indices. The bootstrapping and PLS-SEM estimation settings used for these analyses are reported in Table 7.

Table 7. Bootstrapping and PLS-SEM settings

Setting	Value
Bootstrap subsamples	5,000
Successful bootstrap runs	5,000
Failed bootstrap runs	0
Sampling method	Case resampling with replacement
PLS algorithm	Reflective Mode A
Inner weighting scheme	Path weighting
Maximum iterations	100
Stop criterion	1.00E-07
Confidence interval method	Percentile bootstrap, 95%
Test type	Two-tailed
Significance threshold	p < .05

3. RESULTS

3.1. Measurement model assessment

The measurement model results (Table 8) indicate acceptable reliability and convergent validity, in line with established PLS-SEM reporting guidelines (Hair et al., 2019; Hair et al., 2022). Most out-

Table 8. Measurement model: Reliability and convergent validity

Construct	Items	Cronbach's alpha	rho_A	Composite reliability	AVE	Assessment
AIL	4	0.759	0.753	0.846	0.579	Pass
AIS	4	0.754	0.748	0.843	0.574	Pass
AIT	4	0.787	0.785	0.862	0.611	Pass
AIUM	4	0.767	0.760	0.850	0.587	Pass
PU	3	0.697	0.696	0.832	0.622	Borderline alpha; CR/AVE pass
PEOU	3	0.707	0.706	0.836	0.630	Pass
PME	5	0.816	0.815	0.871	0.576	Pass

Note: AIL = AI Implementation Level; AIS = AI Sophistication; AIT = AI Training for HR Teams; AIUM = AI Utilization Maturity; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

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er loadings exceeded the recommended threshold of 0.70. Two indicators, AIL3 and AIUM4, were classified as borderline based on indicator reliability; however, both had outer loadings above 0.70 and were retained because they were theoretically central to their respective construct domains. Internal consistency reliability was acceptable across the constructs, with composite reliability values ranging from 0.832 to 0.871. Cronbach's alpha values were above 0.70 for all constructs except perceived usefulness, which was marginal at 0.697. Given that rho_A, composite reliability, and AVE for Perceived Usefulness were acceptable, the construct was retained. Convergent validity was established because all AVE values exceeded 0.50.

3.2. Discriminant validity and multicollinearity

Discriminant validity was assessed using the heterotrait-monotrait ratio of correlations (Table 9), which is recommended for variance-based structural equation modeling (Henseler et al., 2015). All HTMT values were below the conservative threshold of 0.85, indicating that the constructs were empirically distinct. Multicollinearity was not a concern because all VIF values were well below the conservative threshold of 3.3 (Table 10).

Table 9. Discriminant validity: HTMT matrix

Construct	AIL	AIS	AIT	AIUM	PU	PEOU	PME
AIL	1	0.551	0.428	0.347	0.481	0.306	0.531
AIS	0.551	1	0.535	0.523	0.539	0.379	0.654
AIT	0.428	0.535	1	0.447	0.589	0.340	0.659
AIUM	0.347	0.523	0.447	1	0.463	0.342	0.640
PU	0.481	0.539	0.589	0.463	1	0.627	0.614
PEOU	0.306	0.379	0.340	0.342	0.627	1	0.473
PME	0.531	0.654	0.659	0.640	0.614	0.473	1

Note: AIL = AI Implementation Level; AIS = AI Sophistication; AIT = AI Training for HR Teams; AIUM = AI Utilization Maturity; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

3.3. Structural model assessment

The structural model (Table 11) produced positive and statistically significant coefficients for all six hypothesized paths. AI implementation level was associated with perceived usefulness (beta = 0.188, t = 3.674, p < .001), as was AI sophistication (beta = 0.222, t = 4.431, p < .001). AI training for HR teams was associated with perceived ease of use (beta = 0.256, t = 4.988, p < .001). Perceived ease of use was associated with perceived usefulness (beta = 0.336, t = 7.466, p < .001), while perceived usefulness (beta = 0.324, t = 6.682, p < .001) and AI utilization maturity (beta = 0.405, t = 9.228, p < .001) were associated with performance management efficiency.

Table 10. Multicollinearity: Inner VIF values

Endogenous construct	Predictor	VIF	Assessment
PU	AIL	1.229	Pass
PU	AIS	1.265	Pass
PU	PEOU	1.101	Pass
PEOU	AIT	1.000	Pass
PME	PU	1.137	Pass
PME	AIUM	1.137	Pass

Note: AIL = AI Implementation Level; AIS = AI Sophistication; AIT = AI Training for HR Teams; AIUM = AI Utilization Maturity; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

Table 11. Structural model: Path coefficients and bootstrap inference

Hypothesis	Path	Coefficient	SE	t	p	95% CI lower	95% CI upper	Decision
H1	AIL → PU	0.188	0.051	3.674	< .001	0.088	0.289	Supported
H2	AIS → PU	0.222	0.050	4.431	< .001	0.127	0.320	Supported
H3	AIT → PEOU	0.256	0.051	4.988	< .001	0.164	0.365	Supported
H4	PEOU → PU	0.336	0.045	7.466	< .001	0.250	0.424	Supported
H5	PU → PME	0.324	0.048	6.682	< .001	0.232	0.419	Supported
H6	AIUM → PME	0.405	0.044	9.228	< .001	0.321	0.493	Supported

Note: PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

3.4. Explanatory power, effect sizes, predictive relevance, and model fit

The model explained 30.3% of the variance in perceived usefulness, 6.6% in perceived ease of use, and 36.0% in performance management efficiency (Table 12). The explanatory power of PME is moderate in an organizational survey model. At the same time, that of PEOU is relatively weak, indicating that AI training explains only a limited proportion of the variation in ease-of-use perceptions. Effect-size analysis (Table 13) showed that most relationships had small effects, while AI utilization maturity had a medium effect on performance management efficiency. Q2 predict values (Table 14) were positive for all endogenous constructs, indicating predictive relevance.

Table 12. Explanatory power: R2 and adjusted R2

Endogenous construct	Predictors	R^2	Adjusted R^2
PU	AIL, AIS, PEOU	0.303	0.296
PEOU	AIT	0.066	0.063
PME	PU, AIUM	0.360	0.356

Note: PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

The model fit results (Table 15) were mixed. The SRMR value of 0.098 exceeded the commonly preferred 0.08 threshold, while the NFI value of 0.870 fell below the preferred 0.90 threshold. Therefore, the global fit indices should be interpreted cautiously. Because PLS-SEM is primarily prediction-oriented, the model assessment was based on the combined evidence from measurement validity, discriminant validity, multicollinearity diagnostics, bootstrapped path significance, explanatory power, effect sizes, and predictive relevance. As reported in Table 11, all six hypothesized relationships were positive and statistically significant, providing support for H1–H6.

4. DISCUSSION

The revised findings provide more theoretically coherent evidence than the original four-path model because the analysis now incorporates the core TAM constructs of perceived usefulness and perceived ease of use. AI implementation level and AI sophistication were both positively associated with perceived usefulness, suggesting that respondents viewed AI-enabled performance management systems as more useful when AI was embedded more broadly and when the systems had stronger analytical, predictive, and feedback capabilities. This is consistent with

Table 13. Effect sizes: f2

Hypothesis	Path	R^2 included	R^2 excluded	f^2	Assessment
H1	AIL → PU	0.303	0.274	0.041	Small
H2	AIS → PU	0.303	0.264	0.056	Small
H4	PEOU → PU	0.303	0.200	0.147	Small
H3	AIT → PEOU	0.066	0.000	0.070	Small
H5	PU → PME	0.360	0.268	0.144	Small
H6	AIUM → PME	0.360	0.216	0.226	Medium

Note: AIL = AI Implementation Level; AIS = AI Sophistication; AIT = AI Training for HR Teams; AIUM = AI Utilization Maturity; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

Table 14. Predictive relevance: Q2 predict

Endogenous construct	Q2 predict	Assessment
PEOU	0.036	Predictive relevance
PU	0.137	Predictive relevance
PME	0.197	Predictive relevance

Note: AIL = AI Implementation Level; AIS = AI Sophistication; AIT = AI Training for HR Teams; AIUM = AI Utilization Maturity; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PME = Performance Management Efficiency.

Table 15. Model fit

Metric	Value	Assessment
SRMR	0.098	Borderline / above preferred .08 threshold
NFI	0.870	Below the preferred .90 threshold

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AI HRM and HR analytics research, which argues that technological value depends on integration into HR routines and decision processes (Budhwar et al., 2022; Marler & Boudreau, 2016; Tambe et al., 2019).

AI training for HR teams was positively associated with perceived ease of use. This finding supports the human-capability dimension of AI adoption: training appears to be associated with greater confidence and clarity in using AI systems. However, the R^2 value for perceived ease of use was low, indicating that training explains only part of ease-of-use perceptions. Other factors, such as system design, vendor support, prior digital skills, and organizational change management, may also shape users' perceptions of AI systems' ease of use.

Consistent with TAM and its later extensions, perceived ease of use was positively associated with perceived usefulness, and perceived usefulness was positively associated with performance management efficiency (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). This suggests that the perceived value of AI-enabled performance management depends not only on the technical presence of AI, but also on whether users consider AI systems practical, efficiency-enhancing, and supportive of decision quality.

AI utilization maturity showed the strongest direct association with performance management efficiency. This indicates that organizations with greater accumulated experience, user familiarity, and AI integration maturity are more likely to report perceived improvements in evaluation accuracy, bias reduction, process speed, productivity tracking, and decision-making. This aligns with strategic AI HRM research suggesting that organizational routines and human-AI complementarities are central to extracting value from AI (Chowdhury et al., 2024; Kim et al., 2024; Raisch & Krakowski, 2021). Because the study uses a cross-sectional survey design, these findings should be interpreted as associations within the model rather than causal effects.

The model fit results were mixed, with SRMR and NFI falling outside preferred thresholds. This does not invalidate the model, but it does mean that the findings should be interpreted with caution and supported by broader measurement and structural diagnostics. Future studies should test alternative model specifications, include additional predictors of ease of use, and use longitudinal or experimental designs to strengthen causal inference (Hair et al., 2022; Henseler et al., 2016).

CONCLUSION AND LIMITATIONS

This study examined how AI-related organizational capabilities and TAM perceptions are associated with perceived performance management efficiency in UK organizations. The revised PLS-SEM results support a TAM-aligned model in which AI implementation level and AI sophistication predict perceived usefulness, AI training predicts perceived ease of use, perceived ease of use predicts perceived usefulness, and perceived usefulness, together with AI utilization maturity, predicts perceived performance management efficiency. The findings suggest that AI-enabled performance management cannot be explained solely by the presence of AI tools. Instead, perceived performance management efficiency is associated with both organizational maturity in AI use and users' perceptions that AI systems are useful and easy to engage with. In practice, this implies that organizations should invest not only in technically sophisticated AI tools but also in training, integration routines, and user-centered implementation practices.

The study is limited by its cross-sectional survey design and reliance on perceived performance management outcomes. Future research should examine longitudinal data, objective HR and productivity indicators, additional predictors of ease of use, and cross-industry or cross-country comparisons. Future studies may also examine employee trust, algorithmic fairness, human–AI feedback, and employee involvement in AI-driven HR decisions (Bennett & Martin, 2026; Taslim et al., 2025; Wang et al., 2026; Xu et al., 2024). These steps would help clarify whether the relationships observed in this study persist over time and under different organizational conditions.

The study is also limited by the absence of control variables in the structural model. Although the sample was described by industry sector, respondent role, and duration of AI utilization, these variables were not incorporated as controls in the PLS-SEM analysis. As a result, the findings should be interpreted as associations among the focal constructs rather than as effects net of organizational or respondent-level characteristics. Future research should test the model's robustness by including control variables such as firm size, industry sector, respondent role, digital maturity, AI usage duration, and organizational age.

AUTHOR CONTRIBUTIONS

Conceptualization: Amina Elshamly.
Data curation: Amina Elshamly.
Formal analysis: Amina Elshamly.
Investigation: Amina Elshamly.
Methodology: Amina Elshamly.
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Validation: Amina Elshamly.
Visualization: Amina Elshamly.
Writing – original draft: Amina Elshamly.
Writing – review & editing: Amina Elshamly.

DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

In preparing this manuscript, the author used ChatGPT to support language editing, structural revision, reference integration, and formatting of manuscript sections. After use, the author processed and edited the text and bears full responsibility for its content.

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APPENDIX A

Table A1. Questionnaire items

Construct	Code	Item	Scale
AI Implementation Level	AIL1	AI is widely used in performance management	5-point Likert
AI Implementation Level	AIL2	HR functions are supported by AI systems	5-point Likert
AI Implementation Level	AIL3	AI tools are integrated into evaluation systems	5-point Likert
AI Implementation Level	AIL4	AI is used for HR decision-making	5-point Likert
AI Sophistication	AIS1	AI systems use advanced analytics	5-point Likert
AI Sophistication	AIS2	AI provides real-time feedback	5-point Likert
AI Sophistication	AIS3	AI predicts performance trends	5-point Likert
AI Sophistication	AIS4	AI systems improve over time	5-point Likert
AI Training for HR Teams	AIT1	HR staff receive AI training	5-point Likert
AI Training for HR Teams	AIT2	Training improves understanding	5-point Likert
AI Training for HR Teams	AIT3	Employees feel confident using AI	5-point Likert
AI Training for HR Teams	AIT4	Training programs are updated regularly	5-point Likert
AI Utilization Maturity	AIUM1	Organization has experience using AI	5-point Likert
AI Utilization Maturity	AIUM2	AI usage has increased over time	5-point Likert
AI Utilization Maturity	AIUM3	Employees are familiar with AI	5-point Likert
AI Utilization Maturity	AIUM4	AI integration has improved	5-point Likert
Performance Management Efficiency	PME1	AI improves evaluation accuracy	5-point Likert
Performance Management Efficiency	PME2	AI reduces bias	5-point Likert
Performance Management Efficiency	PME3	AI increases process speed	5-point Likert
Performance Management Efficiency	PME4	AI improves productivity tracking	5-point Likert
Performance Management Efficiency	PME5	AI enhances decision-making	5-point Likert
Perceived Usefulness	PU1	AI improves job performance	5-point Likert
Perceived Usefulness	PU2	AI enhances decision quality	5-point Likert
Perceived Usefulness	PU3	AI increases efficiency	5-point Likert
Perceived Ease of Use	PEOU1	AI systems are easy to use	5-point Likert
Perceived Ease of Use	PEOU2	Learning AI is simple	5-point Likert
Perceived Ease of Use	PEOU3	Interaction with AI is clear	5-point Likert

Table A2. Content validity

Construct	Conceptual domain covered	Evidence of content validity
AIL	Breadth of AI use in HR/performance management	Items cover use, HR support, evaluation integration, and decision-making.
AIS	Technical capability of AI tools	Items cover analytics, real-time feedback, prediction, and self-improvement.
AIT	Human capability/training	Items cover training availability, understanding, confidence, and updating.
AIUM	Organizational maturity with AI	Items cover experience, increased use, familiarity, and integration maturity.
PME	Perceived performance-management improvement	Items cover accuracy, bias reduction, speed, productivity tracking, and decision-making.
PU	Perceived usefulness	Items cover job performance, decision quality, and efficiency.
PEOU	Perceived ease of use	Items cover ease, simplicity of learning, and clarity of interaction.

Table A3. Measurement model specification

Construct	Code	Measurement specification	Justification	Required assessment
AI Implementation Level	AIL	Reflective	Items reflect the perceived extent to which AI is embedded in performance-management activities.	Outer loadings, alpha, rho_A, CR, AVE, HTMT
AI Sophistication	AIS	Reflective	Items reflect the perceived technical capability of AI systems.	Outer loadings, alpha, rho_A, CR, AVE, HTMT
AI Training for HR Teams	AIT	Reflective	Items reflect the perceived adequacy and effectiveness of AI-related training.	Outer loadings, alpha, rho_A, CR, AVE, HTMT
AI Utilization Maturity	AIUM	Reflective	Items reflect accumulated experience, increased use, employee familiarity, and improved integration.	Outer loadings, alpha, rho_A, CR, AVE, HTMT
Performance Management Efficiency	PME	Reflective	Items reflect perceived improvements in accuracy, bias reduction, speed, tracking, and decision-making.	Outer loadings, alpha, rho_A, CR, AVE, HTMT
Perceived Usefulness	PU	Reflective	Standard TAM construct reflecting perceived performance-related benefits.	Outer loadings, alpha, rho_A, CR, AVE, HTMT
Perceived Ease of Use	PEOU	Reflective	Standard TAM construct reflecting ease, simplicity, and clarity of interaction.	Outer loadings, alpha, rho_A, CR, AVE, HTMT

Table A4. Measurement model: Outer loadings

Construct	Indicator	Outer loading	Indicator reliability	Assessment
AIL	AIL1_Widely_Used_PM	0.750	0.563	OK
AIL	AIL2_HR_Functions_AI_Supported	0.780	0.609	OK
AIL	AIL3_AI_Integrated_Evaluation	0.703	0.494	Borderline
AIL	AIL4_AI_HR_Decision_Making	0.807	0.652	OK
AIS	AIS1_Advanced_Analytics	0.748	0.560	OK
AIS	AIS2_Real_Time_Feedback	0.745	0.555	OK
AIS	AIS3_Predicts_Performance_Trends	0.798	0.637	OK
AIS	AIS4_Systems_Improve_Over_Time	0.736	0.542	OK
AIT	AIT1_HR_Staff_Receive_Training	0.789	0.622	OK
AIT	AIT2_Training_Improves_Understanding	0.802	0.643	OK
AIT	AIT3_Employees_Confident_Using_AI	0.796	0.634	OK
AIT	AIT4_Training_Updated_Regularly	0.738	0.544	OK
AIUM	AIUM1_Experience_Using_AI	0.822	0.676	OK
AIUM	AIUM2_AI_Usage_Increased	0.752	0.565	OK
AIUM	AIUM3_Employees_Familiar_With_AI	0.778	0.606	OK
AIUM	AIUM4_AI_Integration_Improved	0.708	0.501	Borderline
PU	PU1_Improves_Job_Performance	0.781	0.610	OK
PU	PU2_Enhances_Decision_Quality	0.783	0.613	OK
PU	PU3_Increases_Efficiency	0.802	0.643	OK
PEOU	PEOU1_Easy_To_Use	0.788	0.622	OK
PEOU	PEOU2_Learning_AI_Simple	0.818	0.669	OK
PEOU	PEOU3_Interaction_Clear	0.774	0.599	OK
PME	PME1_Evaluation_Accuracy	0.781	0.610	OK
PME	PME2_Reduces_Bias	0.771	0.594	OK
PME	PME3_Process_Speed	0.778	0.605	OK
PME	PME4_Productivity_Tracking	0.750	0.563	OK
PME	PME5_Decision_Making	0.712	0.507	OK

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