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THE IMPACT OF ARTIFICIAL INTELLIGENCE–DRIVEN PERFORMANCE MANAGEMENT ON EMPLOYEE PRODUCTIVITY: THE MEDIATING ROLE OF JOB CRAFTING IN A MULTI-SECTOR STUDY ACROSS INDONESIA

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ABSTRACT
The increasing adoption of artificial intelligence (AI) in performance management systems has reshaped organizational approaches to evaluating and enhancing employee performance. However, empirical evidence regarding the mechanisms through which AI-driven performance management influences employee productivity across diverse industrial sectors remains limited, particularly in emerging economies. This study examines the effect of AI-driven performance management on employee productivity, with job crafting serving as a mediating variable. Using a quantitative explanatory design, data were collected from 170 employees across multiple industries in Indonesia that have implemented AI-based performance management systems. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that AI-driven performance management has a positive and significant direct effect on employee productivity and a strong positive effect on job crafting. Furthermore, job crafting significantly enhances employee productivity and partially mediates the relationship between AI-driven performance management and productivity. These findings suggest that the productivity benefits of AI-based performance management are more effectively realized when employees are supported to proactively redesign their work. This study contributes to the literature on technology-driven human resource management by highlighting the role of employee agency in translating AI-enabled performance systems into improved productivity outcomes.

INTRODUCTIONS

Recent advances in digital technology, particularly Artificial Intelligence (AI), have significantly transformed human resource management, especially in performance management systems. Globally, organizations are increasingly adopting data-driven approaches to enhance workforce efficiency and productivity (Davenport et al., 2020). In Indonesia, this transformation has become more evident alongside rapid economic growth and cross-sector digitalization, with AI being increasingly utilized in business processes and employee performance evaluation (Sabuera, 2024). A McKinsey report (2017) indicates a growing adoption of AI in managerial decision-making, including performance assessment, across Southeast Asia.

Previous studies suggest that AI-based performance management can improve employee productivity through real-time feedback, predictive analytics, and more objective and transparent evaluation systems. However, the effectiveness of AI implementation largely depends on organizational readiness and employees' adaptive capabilities. In this context, job crafting plays a crucial mediating role, as employees proactively modify their tasks and work roles to better align with their individual strengths and goals (Nambisan et al., 2017). Empirical evidence indicates that employees with higher AI literacy are more likely to engage in constructive job crafting, thereby enhancing productivity (Bakker et al., 2012).

Nevertheless, cross-sector empirical findings remain mixed. While AI-driven performance management has demonstrated positive outcomes in technology-intensive industries, its implementation in more traditional sectors often encounters resistance due to concerns over reduced work autonomy and potential job displacement (Vrontis et al., 2021). These variations highlight the need for comprehensive empirical research examining how AI-based performance management influences employee productivity through job crafting, particularly within Indonesia's diverse industrial context, characterized by varying levels of technological readiness and organizational culture.

Artificial Intelligence–Based Performance Management (AI-PM) utilizes AI technologies to enhance the objectivity, accuracy, and timeliness of employee performance evaluation through data-driven, predictive, and prescriptive analytics (Davenport et al., 2020). Drawing on the Ability–Motivation–Opportunity framework, Goal-Setting Theory, and the Job Demands–Resources model, AI-PM is theorized to strengthen employee capabilities, motivation, and job resources by enabling personalized development, real-time feedback, and reduced administrative demands (Baird et al., 2011; Bakker & Demerouti, 2017; Locke & Latham, 2002). Empirical studies generally report positive effects of AI-PM on productivity and engagement, particularly in technology-intensive sectors; however, evidence across traditional industries remains mixed due to variations in technological readiness and organizational culture, underscoring the need for cross-sector empirical investigation in the Indonesian context (Bagis & Yulianeu, 2024; Kuhn et al., 2021).

Job crafting refers to employees' proactive efforts to modify their tasks, work relationships, and perceptions of job meaning to better align with their personal needs, interests, and strengths (Wrzesniewski & Dutton, 2001). Conceptualized within the Job Demands–Resources (JD-R) model, job crafting enables employees to balance job demands and resources by reducing excessive demands while enhancing resources such as autonomy, social support, and developmental opportunities, thereby fostering work engagement and productivity (Bakker & Demerouti, 2017). Empirical studies consistently demonstrate positive associations between job crafting and employee well-being, engagement, and performance across sectors, including evidence from Indonesia (Bakker et al., 2012; Khairawan, 2022; Tims et al., 2013). Moreover, advances in digital technologies, particularly AI-based systems, strengthen job crafting by providing data-driven feedback and insights that facilitate more effective role adaptation, positioning job crafting as a key mechanism linking technology-enabled management practices to enhanced employee.

Employee productivity reflects individuals' contributions to organizational goal attainment through efficient and effective work output. Conceptually, productivity is defined as the ratio between output and input, encompassing both efficiency in resource utilization and effectiveness in achieving performance targets, while also incorporating quality, timeliness, and innovation (Sink et al., 1989). Prior research indicates that employee productivity is influenced by competencies, motivation, technology, and organizational support (Grant & Parker, 2009; Schaufeli, 2017). Empirical evidence further demonstrates that AI-based performance management enhances productivity by providing data-driven feedback and improving work efficiency, whereas job crafting enables employees to align their work with personal strengths, leading to higher engagement and productivity, including within the Indonesian context (Tims et al., 2013).

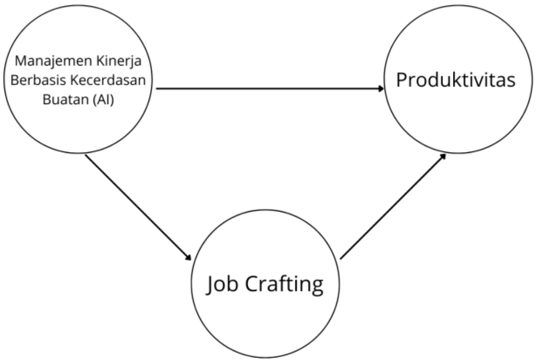

Figure 1. ***Conceptual Framework of the Study***

Despite the growing adoption of artificial intelligence in human resource management, empirical evidence on the effectiveness of AI-driven performance management in improving employee productivity remains fragmented, particularly across diverse industrial sectors in emerging economies. Existing studies predominantly focus on technology-intensive or single-industry contexts and often emphasize direct performance outcomes, providing limited insight into the behavioral mechanisms through which AI-based systems influence employee productivity. As a result, the role of employee agency, especially proactive behaviors such as job crafting, has not been sufficiently examined in relation to AI-driven performance management.

This gap is particularly relevant in the Indonesian context, where organizations exhibit varying levels of digital readiness and institutional maturity. While AI-based performance management systems are increasingly implemented, their outcomes are not uniform and may depend on how employees interpret, adapt to, and utilize AI-generated performance information. Without empirical evidence that accounts for these behavioral dynamics, organizations risk adopting AI-driven systems that emphasize control rather than development, potentially limiting their productivity-enhancing potential. Therefore, a deeper understanding of the conditions and mechanisms through which AI-driven performance management contributes to employee productivity is urgently needed.

Accordingly, this study aims to examine the effect of AI-driven performance management on employee productivity across multiple industrial sectors in Indonesia, with job crafting positioned as a mediating variable. By empirically testing this mediating mechanism, the study seeks to clarify how AI-based performance management systems can be effectively aligned with employee-centered work practices to enhance productivity, thereby addressing both theoretical and practical gaps in the literature on technology-driven human resource management.

METHOD

This study employed a quantitative research design using an explanatory survey approach to investigate the causal relationships among AI-Driven Performance Management (independent variable), Job Crafting (mediating variable), and Employee Productivity (dependent variable). The explanatory survey design was considered suitable for empirically testing hypotheses through structured instruments and objective statistical methods.

The population comprised employees from various industrial sectors in Indonesia working for organizations that have implemented digital or AI-based performance management systems. Such a context was selected to reflect the rapid but uneven adoption of AI in human resource practices across sectors. A purposive sampling technique was applied based on the following criteria:

1. Active employees with a minimum tenure of one year in their current organization.
2. Employed in companies that have adopted digital or AI-based performance management.
3. Willing to complete the questionnaire fully.

The minimum sample size was determined using the 10× rule for Structural Equation Modeling (SEM), where the number of respondents should be at least 10 times the number of indicators in the measurement model. With 21 measurement items, a minimum of 210 respondents was targeted; however, a final sample of 170 respondents was collected based on response completeness and data quality.

The research instrument was developed by adapting validated measurement scales from prior studies to ensure content validity. All items were measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree

Table 1. Measurement of Research Variables

Variable	Dimensions
AI-Driven Performance Management	Data-driven feedback, personalized development, decision-support systems
Job Crafting	Task crafting, relational crafting, cognitive crafting
Employee Productivity	Efficiency, effectiveness, quality, innovation

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS software, chosen for its ability to handle complex models with mediating effects and moderate sample sizes without strict normality requirements. The analysis process included:

1. Measurement Model Evaluation (Outer Model)
   - Convergent validity: factor loadings ≥ 0.70 and AVE ≥ 0.50
   - Discriminant validity: Fornell–Larcker criterion and HTMT ratios
   - Construct reliability: Cronbach's alpha and Composite Reliability ≥ 0.70
2. Structural Model Evaluation (Inner Model)
   - Coefficient of determination (R^2)
   - Effect size (f^2)
   - Predictive relevance (Q^2)
3. Hypothesis Testing
   - Bootstrapping procedure with significance testing (t-statistics and p-values) to assess direct and mediating relationships among variables

RESULTS OF RESEARCH AND DISCUSSION

Measurement Model Evaluation (Outer Model)

The measurement model evaluation was conducted to assess the convergent validity, discriminant validity, and reliability of the constructs, namely AI-Driven Performance Management (X), Job Crafting (M), and Employee Productivity (Y), prior to structural model assessment.

Convergent validity was evaluated by examining indicator loadings and Average Variance Extracted (AVE) values. The results show that all indicators achieved loading values above the recommended threshold of 0.70, indicating that the indicators adequately represent their respective latent constructs. Specifically, the loading values for AI-Driven Performance Management ranged from 0.837 to 0.868, for Job Crafting from 0.824 to 0.848, and for Employee Productivity from 0.816 to 0.874.

Table 2. Indicator Loadings

Construct	Indicator Code	Loading Range
AI-Driven Performance Management (X)	AIHR	0.837–0.868
Job Crafting (M)	JC	0.824–0.848
Employee Productivity (Y)	ICP	0.816–0.874

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In addition, the AVE values for all constructs exceeded the minimum recommended value of 0.50, suggesting an acceptable level of convergent validity. AI-Driven Performance Management recorded an AVE of 0.731, Job Crafting 0.697, and Employee Productivity 0.718

Table 3. Average Variance Extracted (AVE)

Construct	AVE
AI-Driven Performance Management (X)	0.731
Job Crafting (M)	0.697
Employee Productivity (Y)	0.718

Discriminant validity was assessed using the Fornell–Larcker criterion. The results indicate that the square root of AVE for each construct is higher than its correlations with other constructs, suggesting that the constructs are empirically distinct and measure different concepts. The square root of AVE values were 0.930 for AI-Driven Performance Management, 0.930 for Job Crafting, and 0.847 for Employee Productivity.

Table 4. Discriminant Validity (Fornell–Larcker Criterion)

Construct	X	M	Y
AI-Driven Performance Management (X)	**0.930**		
Job Crafting (M)	0.835	**0.930**	
Employee Productivity (Y)	0.911	0.855	**0.847**

Reliability was examined using Cronbach's alpha and Composite Reliability (CR). The findings show that all constructs achieved Cronbach's alpha values above 0.90 and Composite Reliability values above 0.93, which indicate a high level of internal consistency and support the reliability of the measurement instruments.

Table 5. Reliability Analysis

Construct	Cronbach's Alpha	Composite Reliability
AI-Driven Performance Management (X)	> 0.90	> 0.93
Job Crafting (M)	> 0.92	> 0.94
Employee Productivity (Y)	> 0.95	> 0.95

Overall, the results of the measurement model evaluation indicate that the constructs demonstrate acceptable levels of validity and reliability, thereby supporting the suitability of the measurement model for subsequent structural model analysis.

Structural Model Evaluation (Inner Model)

The structural model evaluation was conducted to examine the strength of the relationships among constructs and the model's ability to explain the variance of the endogenous variables. The assessment focused on the coefficient of determination (R^2) and overall model fit indices.

The results indicate that AI-Driven Performance Management explains 86.4% of the variance in Job Crafting ($R^2 = 0.864$). In addition, the combined effects of AI-Driven Performance Management and Job Crafting explain 84.4% of the variance in Employee Productivity ($R^2 = 0.844$). According to established guidelines in PLS-SEM, these R^2 values suggest that the model demonstrates a substantial level of explanatory power for the endogenous constructs.

Table 6. Coefficient of Determination (R^2)

Endogenous Variable	R^2 Value	Interpretation
Job Crafting (M)	0.864	Substantial
Employee Productivity (Y)	0.844	Substantial

Model adequacy was further assessed using goodness-of-fit indicators. The Standardized Root Mean Square Residual (SRMR) value was 0.045 for both the saturated and estimated models, which is below the recommended threshold of 0.08, indicating an acceptable model fit. Additionally, the Normed Fit Index (NFI) value of 0.862 suggests a satisfactory level of model fit relative to a null model.

Table 7. Model Fit Indices

Fit Index	Value	Recommended Threshold
SRMR	0.045	< 0.08

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NFI	0.862	≥ 0.80

Overall, the structural model demonstrates adequate explanatory capability and acceptable model fit, supporting its suitability for subsequent hypothesis testing. These results indicate that the proposed model provides a reasonable representation of the relationships among AI-driven performance management, job crafting, and employee productivity.

Hypothesis Testing

Hypothesis testing was conducted using the bootstrapping procedure to examine the significance of the structural path coefficients. The evaluation was based on path coefficients (β), t-statistics, and p-values to assess the proposed relationships among constructs.

The results of the direct effect analysis indicate that AI-Driven Performance Management has a positive and statistically significant effect on Employee Productivity ($\beta = 0.312$, $t = 3.253$, $p = 0.001$). This finding suggests that the implementation of AI-driven performance management practices is associated with higher levels of employee productivity, thereby supporting Hypothesis 1.

Furthermore, the analysis reveals that AI-Driven Performance Management has a strong and statistically significant effect on Job Crafting ($\beta = 0.930$, $t = 45.958$, $p < 0.001$). This result indicates that AI-based performance management systems substantially encourage employees to engage in proactive job crafting behaviors. Accordingly, Hypothesis 2 is supported.

In addition, Job Crafting is found to have a positive and significant effect on Employee Productivity ($\beta = 0.621$, $t = 6.265$, $p < 0.001$). This finding confirms that employees who actively engage in job crafting tend to demonstrate higher levels of productivity. Thus, Hypothesis 3 (direct effect of job crafting on productivity) is supported and provides a basis for subsequent mediation analysis.

Table 8. Results of Hypothesis Testing

Hypothesis	Structural Path	β	t-value	p-value	Result
H1	AI-PM → Employee Productivity	0.312	3.253	0.001	Supported
H2	AI-PM → Job Crafting	0.930	45.958	< 0.001	Supported
H3	Job Crafting → Employee Productivity	0.621	6.265	< 0.001	Supported

Overall, the results demonstrate that all proposed direct relationships in the structural model are statistically significant and consistent with the theoretical framework. These findings provide empirical support for examining Job Crafting as a mediating mechanism in the relationship between AI-driven performance management and employee productivity.

Mediation Analysis

The mediation analysis was conducted to examine the role of Job Crafting as an intervening variable in the relationship between AI-Driven Performance Management and Employee Productivity. The indirect effect was assessed using the bootstrapping procedure, which is recommended for mediation testing in PLS-SEM.

The results indicate that the indirect effect of AI-driven performance management on employee productivity through job crafting is positive and statistically significant ($\beta = 0.577$, $t = 6.036$, $p < 0.001$). This finding demonstrates that job crafting serves as a significant mediating mechanism in the relationship between AI-driven performance management and employee productivity.

These results suggest that the influence of AI-driven performance management on employee productivity is not limited to a direct effect, but is also transmitted through employees' proactive job redesign behaviors. In this context, AI-based performance management systems appear to provide resources and performance-related information that enable employees to engage in job crafting, which subsequently contributes to higher productivity outcomes.

Given that both the direct effect (AI-PM → Employee Productivity) and the indirect effect via job crafting are statistically significant, the mediation can be classified as partial mediation. This indicates that job crafting strengthens, rather than replaces, the direct relationship between AI-driven performance management and employee productivity.

Table 9. Mediation Analysis ResultS

Path	Indirect Effect (β)	t-value	p-value	Mediation Type
AI-PM → Job Crafting → Employee Productivity	0.577	6.036	< 0.001	Partial Mediation

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Overall, the mediation analysis provides empirical support for the proposed conceptual framework by confirming job crafting as a key behavioral mechanism through which AI-driven performance management enhances employee productivity.

DISCUSSION

This study demonstrates that AI-driven performance management is meaningfully associated with higher levels of employee productivity, both directly and indirectly through job crafting. These findings are well aligned with the Job Demands–Resources (JD-R) framework, which emphasizes that the availability of job resources can stimulate proactive work behaviors and ultimately enhance performance (Bakker & Demerouti, 2017). In this context, AI-driven performance management functions not merely as an evaluation tool but as a strategic resource that supports employees in managing and improving their work.

The positive link between AI-driven performance management and employee productivity corroborates earlier research highlighting the role of artificial intelligence in improving performance-related processes. Prior studies have noted that AI-supported systems enable more timely, objective, and development-oriented feedback, which helps employees better align their efforts with organizational expectations (Davenport et al., 2020; Lu, 2019). Rather than intensifying control, such systems appear to facilitate clarity and focus, allowing employees to perform their tasks more efficiently.

A key contribution of this study lies in demonstrating the mediating role of job crafting in this relationship. The results indicate that AI-driven performance management encourages employees to actively reshape their tasks, social interactions, and perceptions of work, which in turn contributes to higher productivity. This finding is consistent with the foundational work of Wrzesniewski and Dutton (2001) and subsequent empirical studies showing that job crafting emerges when employees perceive sufficient resources and autonomy in their work environment (Tims et al., 2013).

The strong association between AI-driven performance management and job crafting suggests that technology-enabled systems may enhance employees' capacity to engage in proactive job redesign. By providing performance data, developmental insights, and clearer role expectations, AI-driven systems create conditions that support job crafting behaviors. This observation aligns with Bakker et al. (2012), who argue that supportive organizational contexts increase the likelihood of job crafting and its positive outcomes. More recent evidence also indicates that digital technologies can amplify employee agency when they are designed to support learning and decision-making rather than surveillance alone (Wang et al., 2025).

Within the Indonesian cross-sector setting, these findings underline the importance of employee involvement in the successful implementation of AI-driven performance management. Consistent with previous studies conducted in Indonesia, the effectiveness of digital human resource practices appears to depend on how employees respond and adapt to such systems (Pratama et al., 2023). In this regard, job crafting serves as a critical behavioral mechanism that bridges advanced performance management technologies and employee productivity.

Practical Implications

The results of this study indicate that AI-driven performance management contributes to employee productivity not only through direct performance evaluation but also by enabling proactive job crafting behaviors. Practically, this finding suggests that organizations should position AI-based performance management systems as developmental tools rather than purely control-oriented mechanisms. The provision of real-time, data-driven feedback and personalized performance insights can support employees in adjusting their tasks, work strategies, and role boundaries in ways that enhance productivity.

Moreover, the significant mediating role of job crafting implies that the effectiveness of AI-driven performance management depends on organizational support for employee autonomy and proactive work redesign. Human resource managers should integrate AI-based performance systems with policies that encourage flexibility, role clarity, and employee participation. Training initiatives aimed at improving employees' ability to interpret and utilize AI-generated feedback are also critical to ensure that technological resources translate into productive work behaviors.

Limitations

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Several limitations should be considered when interpreting the findings of this study. First, the cross-sectional design restricts causal interpretation and does not capture changes in employee behavior over time. Future studies employing longitudinal designs would provide stronger evidence regarding the dynamic effects of AI-driven performance management on job crafting and productivity. Second, the use of self-reported data may introduce common method bias, suggesting the need for future research to incorporate objective performance indicators or multi-source assessments.

Additionally, the study sample was limited to organizations that had already adopted digital or AI-based performance management systems, which may constrain the generalizability of the results to less technologically mature contexts. Finally, this research focused solely on job crafting as a mediating variable; future studies are encouraged to examine additional psychological and organizational factors, such as trust in AI, perceived fairness, or leadership support, to further explain the effectiveness of AI-driven performance management.

Overall, this study enriches the existing literature by integrating AI-driven performance management and job crafting within a unified explanatory framework. The findings suggest that the productivity-enhancing potential of AI-driven systems is more likely to be realized when employees are enabled to proactively shape their work. This perspective extends the JD-R framework by highlighting the interaction between technological resources and employee agency in contemporary organizational contexts

CONCLUSION

This study provides empirical evidence that AI-driven performance management positively influences employee productivity across multiple industrial sectors in Indonesia, both directly and indirectly through job crafting. The findings contribute to the literature on technology-driven human resource management by demonstrating that job crafting functions as a key behavioral mechanism that translates AI-based performance systems into tangible productivity outcomes. By integrating the Job Demands–Resources framework with AI-enabled performance management, this research extends existing theoretical perspectives by highlighting the interactive role of technological resources and employee agency in contemporary organizations.

From a practical and policy perspective, the results suggest that organizations and decision-makers should adopt AI-driven performance management systems as developmental and employee-centered tools rather than purely evaluative instruments. Policies that promote employee autonomy, role flexibility, and access to meaningful performance feedback are essential to encourage job crafting behaviors and maximize productivity gains. In practice, organizations are advised to complement AI-based systems with targeted training programs that enhance employees' ability to interpret AI-generated insights and proactively redesign their work.

Despite its contributions, this study is subject to limitations related to its cross-sectional design, reliance on self-reported data, and focus on organizations with prior AI adoption, which may limit causal inference and generalizability. Future research is therefore encouraged to employ longitudinal and mixed-method approaches, incorporate objective performance measures, and examine additional contextual factors such as trust in AI, perceived algorithmic fairness, and leadership support to deepen understanding of the long-term implications of AI-driven performance management.

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