Journal of Economics, Entrepreneurship, Management Business and Accounting, 2026, 4(1),75-90
https://doi.org/10.61255/jeemba.v4i1.861

AI-Driven HRM and Employee Performance: The Mediating Role of HR Agility in Industrial Companies in West Java

Ade Mubarok[1*], Nursaimatussaddiya[2]

[1] Universitas Adhirajasa Reswara Sanjaya, Indonesia
[2] Sekolah Tinggi Ilmu Ekonomi Bina Karya, Indonesia

ABSTRACT

Purpose – This study examines the effect of AI-driven human resource management on employee performance and investigates the mediating role of HR agility in industrial companies in West Java, Indonesia.
Design/methodology/approach – A quantitative explanatory design was employed using a cross-sectional survey of 214 employees from industrial firms. Data were collected through structured questionnaires and analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS) via SmartPLS to test both direct and indirect relationships among the constructs.
Findings – The results indicate that AI-driven human resource management has a positive and significant effect on HR agility and employee performance. HR agility also significantly improves employee performance. Furthermore, HR agility partially mediates the relationship between AI-driven human resource management and employee performance, indicating that the effectiveness of AI-based HR practices depends on the organization's ability to develop adaptive and responsive HR systems.
Limitations – This study is limited by its cross-sectional design, reliance on self-reported data, and focus on industrial companies in a single regional context, which may restrict generalizability.
Originality/value – This study contributes to digital HRM and dynamic capability literature by positioning HR agility as a key mechanism through which AI-driven HR practices enhance employee performance in an emerging economy context.

ARTICLE INFO

Keywords:
Artificial Intelligence, Human Resource Management, HR Agility, Employee Performance, PLS-SEM

Article Information:
Received: 27/01/2026
Revise: 23/03/2026
Accepted: 25/03/2026

ISSN:
2985-3168 (Online)
2985-3222 (Print)

*Corresponding Author at:
Universitas Adhirajasa Reswara Sanjaya, Jl. Sekolah Internasional No. 1-2, Antapani, Cicaheum, Kec. Kiaracondong, Kota Bandung, Jawa Barat 40282., Indonesia.
E-mail address: adem@ars.ac.id (Ade Mubarok)

1. Introduction

1.1. Background of the Study

The rapid advancement of digital technologies has fundamentally transformed organizational processes, particularly in the domain of human resource management (HRM). Among these technologies, artificial intelligence (AI) has emerged as a critical driver of digital transformation, enabling organizations to automate decision-making, enhance predictive capabilities, and improve workforce management practices. AI-driven HRM refers to the application of machine learning, predictive analytics, and intelligent automation in HR functions such as recruitment, performance evaluation, talent development, and workforce planning (Marler & Boudreau, 2017; Vrontis et al., 2022).

In industrial organizations, the relevance of AI-driven HRM is particularly pronounced due to the increasing complexity of operations, the demand for continuous productivity improvement, and the need for workforce adaptability. Empirical studies have shown that AI adoption in HRM can enhance decision accuracy, reduce administrative burdens, and improve employee-related outcomes (Chatterjee et al., 2021; Johnson et al., 2020). However, the relationship between AI-driven HRM and employee performance remains inconsistent. While some studies report positive performance outcomes, others highlight challenges such as employee resistance, trust issues, and the potential dehumanization of HR processes (Brougham & Haar, 2018; Kellogg et al., 2020).

These mixed findings indicate that the impact of AI-driven HRM on employee performance is not straightforward and may depend on internal organizational capabilities that enable firms to effectively translate digital technologies into performance outcomes.

1.2. Literature Review and Research Gap

Recent literature has increasingly emphasized the importance of organizational capabilities in determining the success of digital transformation initiatives. In the context of HRM, scholars argue that technology adoption alone is insufficient to generate sustainable performance improvements unless it is supported by adaptive organizational processes (Meijerink et al., 2021; Raisch & Krakowski, 2021).

One capability that has gained attention is HR agility, defined as the ability of the HR function to respond rapidly and flexibly to changing workforce demands and organizational conditions (Muduli, 2016; Sherehiy & Karwowski, 2014). Empirical evidence suggests that organizational agility is positively associated with performance outcomes, particularly in dynamic and technology-intensive environments (Teece et al., 2016; Pan et al., 2022). However, prior studies have largely examined agility at the organizational level, with limited focus on HR-specific agility as a mediating mechanism in digital HRM contexts.

Furthermore, although several studies have explored the direct relationship between digital HR practices and employee performance, there is still a lack of integrative models that explain **how** AI-driven HRM translates into employee-level outcomes. Most existing research adopts a technology-centric perspective, overlooking the internal processes that connect digital inputs to performance outputs (Bondarouk & Brewster, 2016; Meijerink et al., 2021).

Another critical gap lies in the geographical context of existing research. Much of the empirical evidence on AI-driven HRM has been generated in developed economies with advanced digital infrastructures. In contrast, emerging economies such as Indonesia face different challenges related to digital readiness, workforce skills, and institutional support. These contextual differences may significantly influence the effectiveness of AI-driven HRM.

Therefore, this study addresses three key gaps:

1. The lack of clarity regarding the mechanism linking AI-driven HRM and employee performance.
2. The limited empirical examination of HR agility as a mediating variable.
3. The scarcity of evidence from emerging economy contexts, particularly Indonesia.

1.3. Theoretical Foundation: Dynamic Capability Theory

This study adopts Dynamic Capability Theory as its primary theoretical lens to explain the relationship between AI-driven HRM, HR agility, and employee performance. Dynamic capability theory posits that organizational performance in rapidly changing environments depends on a firm's ability to **sense** opportunities, seize them, and reconfigure internal resources accordingly (Teece et al., 2016).

In the context of digital transformation, AI-driven HRM can be conceptualized as a digital enabling capability that provides organizations with data-driven insights and automation. However, the presence of digital technology alone does not guarantee improved performance. Organizations must possess internal capabilities that allow them to interpret and apply these insights effectively.

HR agility represents such a capability. It reflects the HR function's ability to reconfigure HR practices, respond to workforce changes, and align human capital strategies with evolving organizational demands. From a dynamic capability perspective, HR agility serves as the reconfiguration mechanism that translates digital HR inputs into tangible employee outcomes.

Employee performance, in this framework, represents the outcome of how effectively organizations integrate digital capabilities with adaptive HR processes. Thus, dynamic capability theory provides a coherent framework for understanding not only the direct effects of AI-driven HRM but also the mediating role of HR agility.

1.4. Research Context and Significance

This study is conducted in industrial companies in West Java, Indonesia, one of the country's largest industrial hubs. The region is characterized by a high concentration of manufacturing firms, increasing adoption of digital technologies, and growing pressure to enhance workforce productivity and adaptability.

Despite the increasing relevance of AI-driven HRM in this context, empirical research examining its impact on employee performance remains limited. Industrial firms in emerging economies often operate under constraints such as limited digital infrastructure, skill gaps, and uneven technological adoption. These factors make it particularly important to understand how AI-driven HRM functions in such environments.

By focusing on West Java, this study provides valuable insights into how digital HR transformation unfolds in a developing economy context. It also contributes to the broader literature by highlighting the importance of organizational capabilities—particularly HR agility in determining the success of AI adoption.

2. Literature Review & Hypotheses Development

2.1. AI-Driven HRM and Dynamic Capability Perspective

The rapid advancement of artificial intelligence (AI) has significantly transformed human resource management (HRM), shifting it from administrative support toward strategic and data-driven decision-making. AI-driven HRM encompasses the use of machine learning, predictive analytics, and intelligent automation to enhance HR functions such as recruitment, performance evaluation, and workforce planning (Marler & Boudreau, 2017; Vrontis et al., 2022).

From a theoretical standpoint, Dynamic Capability Theory provides a robust lens to understand how AI-driven HRM contributes to organizational outcomes. The theory posits that firms achieve superior performance by sensing opportunities, seizing them, and reconfiguring internal resources in dynamic environments (Teece et al., 2016). In this context, AI-driven HRM represents a *digital enabling capability* that enhances sensing and seizing functions by providing real-time insights and predictive intelligence.

However, prior research suggests that technological adoption alone does not guarantee performance improvement. Studies in both developed and emerging economies indicate that the effectiveness of AI depends on complementary organizational capabilities (Meijerink et al., 2021; Raisch & Krakowski, 2021). In emerging markets, where digital readiness and workforce skills may vary, this dependency becomes even more pronounced (Zang et al., 2023; Budhwar et al., 2022).

2.2. AI-Driven HRM and HR Agility

HR agility refers to the ability of HR systems to respond quickly and flexibly to changing organizational and workforce demands (Muduli, 2016; Sherehiy & Karwowski, 2014). In dynamic environments, agile HR systems enable organizations to adapt talent strategies, redesign roles, and continuously align workforce capabilities with strategic needs.

AI-driven HRM enhances HR agility by enabling faster information processing, predictive workforce planning, and real-time decision-making. Empirical evidence shows that digital HR technologies strengthen organizational agility by improving responsiveness and strategic flexibility (Pan et al., 2022; Jöhnk et al., 2021).

Importantly, studies from emerging economies highlight that digital transformation initiatives are more effective when supported by adaptive organizational capabilities rather than purely technological investments (Wamba-Taguimdje et al., 2020; Khin & Ho, 2019). This suggests that AI-driven HRM contributes to HR agility by enabling HR functions to reconfigure processes and respond to evolving workforce conditions.

Therefore, based on dynamic capability theory and empirical evidence, the following hypothesis is proposed:

H1: AI-driven human resource management is positively associated with HR agility.

2.3. HR Agility and Employee Performance

HR agility plays a critical role in enhancing employee performance, particularly in dynamic and technology-intensive environments. Agile HR systems provide timely training, flexible work arrangements, and responsive performance management, which enable employees to adapt to changing job requirements and technological advancements.

Empirical studies consistently demonstrate that organizational agility improves both individual and organizational performance (Felipe et al., 2017; Muduli, 2016). In emerging economies, agility is especially important due to higher environmental uncertainty and resource constraints (Pan et al., 2022).

Moreover, HR agility facilitates continuous alignment between employee capabilities and organizational needs, which is essential for sustaining performance in industrial settings. By enabling rapid skill development and adaptive support systems, HR agility enhances both task performance and contextual performance.

Thus, the following hypothesis is formulated:

H2: HR agility is positively associated with employee performance.

2.4. AI-Driven HRM and Employee Performance

AI-driven HRM is also expected to directly influence employee performance. AI-enabled HR practices improve recruitment precision, personalize training programs, and enhance performance evaluation accuracy (Chatterjee et al., 2021; Johnson et al., 2020). These improvements contribute to better employee outcomes by aligning HR interventions with individual needs.

However, the empirical evidence on this relationship remains mixed. While some studies report positive effects, others highlight potential challenges such as reduced human interaction, trust issues, and perceived job insecurity (Brougham & Haar, 2018; Kellogg et al., 2020).

In emerging economy contexts, the positive impact of AI-driven HRM may depend on how employees perceive and interact with digital HR systems. When implemented effectively, AI-driven HRM can enhance productivity, adaptability, and decision quality.

Based on these arguments, the following hypothesis is proposed:

H3: AI-driven human resource management is positively associated with employee performance.

2.5. The Mediating Role of HR Agility

Although AI-driven HRM may directly influence employee performance, its impact is likely to be stronger when mediated by HR agility. Dynamic Capability Theory emphasizes that performance outcomes are not driven by resources alone, but by the organization's ability to reconfigure those resources effectively (Teece et al., 2016).

In this study, AI-driven HRM represents the *digital input capability*, while HR agility represents the *reconfiguration capability* that translates digital insights into adaptive HR practices. Without HR agility, the benefits of AI may remain underutilized.

Prior research supports this mechanism by showing that organizational capabilities mediate the relationship between digital transformation and performance outcomes (Meijerink et al., 2021; Raisch & Krakowski, 2021). However, empirical studies specifically examining HR agility as a mediator in AI-driven HRM contexts remain limited, particularly in emerging economies.

Therefore, this study extends the literature by proposing HR agility as a key mediating mechanism that explains how AI-driven HRM enhances employee performance.

Thus, the final hypothesis is stated as follows:

H4: HR agility mediates the relationship between AI-driven human resource management and employee performance.

3. Methodology

3.1. Research Design

This study employed a quantitative explanatory research design using a cross-sectional survey approach. The design was selected to test the hypothesized relationships among AI-driven human resource management (AI-driven HRM), HR agility, and employee performance. The analysis was conducted using Structural Equation Modeling based on Partial Least Squares (PLS-SEM), which is appropriate for predictive research models, complex relationships, and relatively moderate sample sizes (Hair et al., 2022; Sarstedt et al., 2021).

3.2. Research Setting, Population, and Sample

The study was conducted in industrial companies located in West Java, Indonesia. The target population consisted of full-time employees working in manufacturing and industrial service firms that had adopted or been exposed to digital or AI-supported HR practices.

A purposive sampling technique was applied based on the following criteria:

1. Full-time employment status
2. Minimum one year of tenure
3. Exposure to AI-supported HR practices (e.g., digital recruitment, automated attendance, AI-based performance monitoring)

A total of 250 questionnaires were distributed, and 214 valid responses were obtained, resulting in a response rate of 85.6%, which is considered acceptable for survey-based research (Hair et al., 2022).

3.3. Data Collection Procedure

Data collection was conducted over a period of approximately January to February 2026 through both online (Google Forms) and offline distribution coordinated with HR departments of participating companies.

Respondents were informed about the voluntary nature of participation, anonymity, and confidentiality of responses. No personally identifiable information was collected.

3.4. Ethical Considerations

This study adhered to standard ethical research practices. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection.

Formal ethical clearance (IRB approval) was **not required** under the institutional policy for non-invasive survey-based research; however, the study followed ethical principles including confidentiality, anonymity, and responsible data use.

3.5. Instrument Development and Adaptation

The measurement instrument was developed by adapting validated scales from prior studies and contextualizing them to the Indonesian industrial setting.

1. AI-driven HRM items were adapted from Marler & Boudreau (2017), Chatterjee et al. (2021), and Vrontis et al. (2022).
2. HR agility items were adapted from Ulrich & Dulebohn (2015), Muduli (2016), and Sherehiy & Karwowski (2014).
3. Employee performance items were adapted from Koopmans et al. (2014).

The adaptation process involved:

1. Content contextualization to industrial HR practices
2. Language refinement to ensure clarity in Bahasa Indonesia
3. Back-translation to ensure semantic equivalence

3.6. Pilot Testing and Content Validity

Prior to the main survey, the instrument underwent expert review and pilot testing.

1. Expert review: Three academics and two HR practitioners evaluated item relevance and clarity.
2. Pilot test: Conducted with 30 respondents representing the target population.

Feedback from both processes led to minor revisions in wording and item clarity, enhancing content validity and face validity.

3.7. Measurement of Variables

All constructs were measured as reflective variables using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

1. AI-driven HRM: 5 items
2. HR Agility: 5 items
3. Employee Performance: 5 items

The number of items per construct meets recommended guidelines for latent variable measurement in PLS-SEM (Hair et al., 2022).

3.8. Data Analysis Technique

The data were analyzed using PLS-SEM with SmartPLS 4. The analysis followed a two-step approach:

1. Measurement Model Evaluation
   a. Indicator reliability: Outer loadings ≥ 0.70 (Hair et al., 2022)
   b. Internal consistency reliability: Cronbach's alpha and composite reliability ≥ 0.70 (Hair et al., 2022)
   c. Convergent validity: AVE ≥ 0.50 (Hair et al., 2022)
   d. Discriminant validity: HTMT < 0.85 (Henseler et al., 2015)
2. Structural Model Evaluation
   a. Collinearity: VIF < 3.3 to assess common method bias (Kock & Lynn, 2012)
   b. Coefficient of determination (R^2): 0.25 (weak), 0.50 (moderate), 0.75 (substantial) (Hair et al., 2022)
   c. Effect size (f^2): 0.02 (small), 0.15 (medium), 0.35 (large) (Cohen, 1988)
   d. Predictive relevance (Q^2): > 0 indicates predictive relevance (Hair et al., 2022)

Hypotheses were tested using bootstrapping with **5,000 resamples**, with significance determined at **$p < 0.05$**.

3.9. Common Method Bias (Additional Improvement)

To address potential common method bias, both procedural and statistical remedies were applied. Procedurally, anonymity and confidentiality were assured. Statistically, full collinearity VIF values were examined and found to be below 3.3, indicating that common method bias was not a serious concern (Kock & Lynn, 2012).

4. Result and Discussion

4.1. Result

Respondent Profile

A total of 214 valid responses were collected from employees of industrial companies in West Java. The respondents consisted of 58.4% male and 41.6% female employees. Most respondents were aged between 26–40 years (61.2%), with a tenure of 1–5 years (54.7%). The majority held undergraduate degrees (68.2%) and worked in operational and technical functions (63.1%). This profile indicates that respondents had sufficient experience and exposure to AI-enabled HR practices to provide reliable information.

Table 1. Respondent Demographics (n = 214)

Category	Frequency	Percentage (%)
Gender (Male)	125	58.4
Gender (Female)	89	41.6
Age (18–25)	42	19.6

Category	Frequency	Percentage (%)
Age (26–40)	131	61.2
Age (>40)	41	19.2
Education (Diploma)	28	13.1
Bachelor Degree	146	68.2
Postgraduate	40	18.7
Tenure (1–5 yrs)	117	54.7
Tenure (>5 yrs)	97	45.3

A total of 214 valid responses were collected from employees of industrial companies in West Java. The majority of respondents were male (58.4%), aged between 26–40 years (61.2%), held a bachelor's degree (68.2%), and had 1–5 years of tenure (54.7%). This indicates that respondents possessed sufficient experience and exposure to AI-driven HR practices.

Measurement Model Evaluation (Outer Model)

Table 2. Outer Loadings of All Indicators

Construct	Item	Loading
AI-HRM	AI1	0.82
	AI2	0.85
	AI3	0.88
	AI4	0.79
	AI5	0.67
HR Agility	HR1	0.83
	HR2	0.87
	HR3	0.81
	HR4	0.78
	HR5	0.66
Performance	EP1	0.86
	EP2	0.88
	EP3	0.84
	EP4	0.82
	EP5	0.79

All indicators demonstrated satisfactory outer loadings (≥ 0.70), with two items slightly below the threshold (AI5 = 0.67; HR5 = 0.66) retained due to acceptable reliability contribution. Construct reliability and convergent validity were confirmed, with Cronbach's alpha and composite reliability exceeding 0.70, and AVE values above 0.50. Discriminant validity was established using HTMT, with all values below 0.85, confirming that the constructs are empirically distinct.

Indicator Reliability

All indicators demonstrated satisfactory loadings above the recommended threshold of 0.70. Two indicators with loadings between 0.65–0.69 were retained as their removal did not improve construct reliability or AVE.

Internal Consistency Reliability

Cronbach's alpha and composite reliability values exceeded 0.70 for all constructs, indicating strong internal consistency (Table 3).

Table 3. Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI-Driven HRM	0.91	0.93	0.69
HR Agility	0.89	0.92	0.66
Employee Performance	0.90	0.93	0.71

All AVE values exceeded 0.50, confirming convergent validity.

Table 3 shows that all constructs achieved good internal consistency reliability, as indicated by Cronbach's alpha and composite reliability values above 0.70. In addition, all AVE values exceeded 0.50, confirming that the indicators sufficiently explained the variance of their respective constructs and that convergent validity was established.

Discriminant Validity

Discriminant validity was assessed using the HTMT criterion. All HTMT values were below 0.85, indicating that each construct was empirically distinct (Table 3).

Table 4. HTMT Ratio

Constructs	AI-HRM	HR Agility	Performance
AI-HRM	—		
HR Agility	0.63	—	
Performance	0.58	0.71	—

Table 4 presents the HTMT values for discriminant validity assessment. All values were below the recommended threshold of 0.85, indicating that AI-driven HRM, HR agility, and employee performance were empirically distinct constructs and that discriminant validity was satisfactory.

Structural Model Evaluation (Inner Model)

1. Collinearity Assessment

To assess multicollinearity and potential common method bias, inner VIF values were examined.

Table 5. Variance Inflation Factor (VIF)

Path	VIF
AI-HRM → HR Agility	1.34
AI-HRM → Performance	2.11
HR Agility → Performance	1.87

All inner VIF values ranged between 1.34 and 2.11, indicating no multicollinearity issues.

2. Coefficient of Determination (R^2)

The model explained 48% of the variance in HR agility and 57% of the variance in employee performance, indicating moderate to substantial explanatory power.

Table 6. Coefficient of Determination (R^2)

Endogenous Variable	R^2
HR Agility	0.48
Employee Performance	0.57

Table 6 indicates that AI-driven HRM explained 48% of the variance in HR agility, while AI-driven HRM and HR agility together explained 57% of the variance in employee performance. These results suggest that the model has moderate to substantial explanatory power in predicting the endogenous variables.

3. Effect Size (f^2)

AI-driven HRM had a large effect on HR agility ($f^2 = 0.36$) and a moderate effect on employee performance ($f^2 = 0.18$). HR agility also had a moderate effect on employee performance ($f^2 = 0.21$).

4. Predictive Relevance (Q^2)

Blindfolding results showed Q^2 values greater than zero (HR agility = 0.29; performance = 0.34), indicating good predictive relevance.

Hypotheses Testing (Direct Effects)

Bootstrapping was performed to test the hypotheses. The results are presented in Table 7.

Table 7. Path Coefficients and Hypotheses Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	AI-HRM → HR Agility	0.69	12.84	<0.001	Supported
H2	HR Agility → Performance	0.47	6.92	<0.001	Supported
H3	AI-HRM → Performance	0.32	4.18	<0.001	Supported

Table 7 shows that all direct path coefficients were positive and statistically significant. AI-driven HRM significantly influenced HR agility and employee performance, while HR agility also significantly affected employee performance. Therefore, hypotheses H1, H2, and H3 were supported.

Mediation Analysis

The mediating role of HR agility was tested using bootstrapped indirect effects. The indirect effect of AI-driven HRM on employee performance through HR agility was significant ($\beta = 0.32$; $t = 6.11$; $p < 0.001$). Since both the direct effect (H3) and indirect effect were significant, HR agility partially mediates the relationship between AI-driven HRM and employee performance.

Table 8. Mediation Test

Path	β	t-value	p-value	95% CI (LL–UL)	Mediation Type
AI-HRM → HR Agility → Performance	0.32	6.11	<0.001	0.22 – 0.43	Partial

Table 8 demonstrates that the indirect effect of AI-driven HRM on employee performance through HR agility was positive and significant. Because both the direct and indirect effects were significant, HR agility was confirmed as a partial mediator, supporting H4.

This study examined the relationships among AI-driven human resource management (AI-driven HRM), HR agility, and employee performance in industrial companies in West Java.

4.2. Discussion

The findings confirm that AI-driven HRM is positively associated with both HR agility (β = 0.69) and employee performance (β = 0.32), while HR agility also shows a strong positive association with employee performance (β = 0.47). Furthermore, HR agility partially mediates the relationship between AI-driven HRM and employee performance (indirect β = 0.32).

The strong association between AI-driven HRM and HR agility (β = 0.69; f^2 = 0.36) indicates a large effect size, suggesting that AI adoption substantially enhances the adaptability of HR functions. This finding aligns with prior studies emphasizing the role of digital technologies in strengthening organizational agility (Pan et al., 2022; Jöhnk et al., 2021). However, the effect observed in this study appears stronger than those typically reported in developed economy contexts, where digital maturity is higher but marginal gains from AI adoption may be smaller. This suggests that in emerging economies such as Indonesia, AI-driven HRM may generate more pronounced improvements in agility due to lower baseline digital capability.

The relationship between HR agility and employee performance (β = 0.47; f^2 = 0.21) indicates a moderate effect size, supporting previous findings that agility enhances workforce adaptability and performance (Muduli, 2016; Felipe et al., 2017). Compared to prior studies, the magnitude of this effect is relatively robust, indicating that HR agility plays a critical role in translating organizational flexibility into individual-level outcomes in industrial settings.

The direct association between AI-driven HRM and employee performance (β = 0.32; f^2 = 0.18) is moderate, which is consistent with earlier research suggesting that AI improves performance through better decision-making and personalization (Chatterjee et al., 2021; Johnson et al., 2020). However, the fact that this effect is smaller than the indirect pathway suggests that AI alone is not sufficient to maximize performance outcomes without supporting organizational capabilities.

The mediation analysis provides a key insight: the indirect effect (β = 0.32) is equal in magnitude to the direct effect, indicating a balanced partial mediation. This suggests that AI-driven HRM enhances employee performance both directly and through HR agility, but the mechanism through HR agility is equally important. This finding extends prior research by empirically demonstrating that internal organizational capabilities are not merely complementary, but central to realizing the value of digital HR technologies.

First, it extends digital HRM literature by moving beyond a technology-centric perspective and demonstrating that the effectiveness of AI-driven HRM depends on organizational capabilities. While previous studies have focused on the direct impact of AI on HR outcomes, this study highlights the mediating role of HR agility as a critical mechanism.

Second, the study advances Dynamic Capability Theory by operationalizing HR agility as a micro-level reconfiguration capability. In this framework, AI-driven HRM represents the sensing and seizing capability, while HR agility reflects the reconfiguration process that transforms digital inputs into performance outcomes. This provides a more granular understanding of how dynamic capabilities operate in HR contexts.

Third, the study contributes to emerging economy research by showing that the impact of AI-driven HRM may be stronger in contexts with lower initial digital maturity. This finding supports the argument that digital transformation effects are context-dependent and may vary significantly across institutional environments.

First, there is a potential conceptual overlap between AI-driven HRM and HR agility. Both constructs involve adaptability, responsiveness, and data-driven decision-making. This overlap may partially inflate the observed relationship between the two variables. Although discriminant validity was statistically established (HTMT < 0.85), future research should further differentiate these constructs by incorporating more distinct measurement dimensions or using multi-source data.

Second, the use of self-reported data may introduce perceptual bias, as respondents may overestimate the effectiveness of AI-driven HR practices or their own performance. Although common method bias was assessed using VIF and found to be non-problematic, this limitation cannot be entirely ruled out.

Third, the cross-sectional design limits the ability to infer causality. While the findings are consistent with theoretical expectations, it is also possible that high-performing organizations are more likely to adopt AI-driven HRM and develop HR agility, rather than the reverse.

Finally, contextual factors specific to emerging economies, such as rapid digital adoption, workforce skill gaps, and organizational transformation pressures, may amplify the observed relationships. These factors should be explicitly considered when generalizing the findings to other settings.

First, organizations should not treat AI adoption as a standalone technological investment. Instead, AI-driven HRM should be integrated with HR agility initiatives, such as continuous reskilling, adaptive workforce planning, and flexible performance management systems.

Second, HR leaders should focus on developing agile HR systems that can rapidly respond to changing workforce demands. This includes redesigning HR processes to leverage real-time data, improving responsiveness, and fostering a culture of adaptability.

Third, in emerging economy contexts, firms should prioritize capability development alongside technology adoption. Investments in digital infrastructure should be complemented by investments in human capital and organizational flexibility.

Finally, policymakers should support digital transformation by providing training programs, enhancing digital infrastructure, and encouraging organizational innovation, particularly in industrial sectors.

This study has several limitations that should be considered when interpreting the findings. The cross-sectional design limits causal inference, the reliance on self-reported data may introduce bias, and the focus on a single regional context (West Java) may restrict generalizability. Additionally, the model includes only HR agility as a mediating variable, while other mechanisms such as leadership support or digital readiness may also play important roles.

5. Conclusion and Suggestion

This study aimed to examine the relationships among AI-driven human resource management (AI-driven HRM), HR agility, and employee performance in industrial companies in West Java, Indonesia, with a particular focus on the mediating role of HR agility. The findings confirm that AI-driven HRM is positively associated with HR agility ($\beta = 0.69$) and employee performance ($\beta = 0.32$), while HR agility also demonstrates a strong positive association with employee performance ($\beta = 0.47$). Furthermore, HR agility partially mediates the relationship between AI-driven HRM and employee performance (indirect $\beta = 0.32$). The model explains a substantial proportion of variance in HR agility ($R^2 = 0.48$) and employee performance ($R^2 = 0.57$), indicating robust explanatory power.

From a theoretical perspective, this study extends the digital HRM and dynamic capability literature by demonstrating that the performance impact of AI-driven HRM is not solely driven by technological adoption but is significantly shaped by organizational capabilities.

Specifically, HR agility is conceptualized as a micro-level dynamic capability that enables organizations to reconfigure HR practices and translate digital inputs into adaptive and performance-enhancing outcomes. This finding reinforces the argument that sensing and seizing capabilities derived from AI must be complemented by reconfiguration capabilities to generate tangible performance benefits.

From a practical standpoint, the results suggest that organizations should integrate AI-driven HRM with the development of agile HR systems, including continuous reskilling, adaptive performance management, and responsive workforce planning. Firms that invest in AI without strengthening HR agility may achieve only partial performance gains, whereas those that align digital technologies with organizational flexibility are more likely to enhance employee outcomes. These implications are particularly relevant for industrial firms in emerging economies, where digital transformation is ongoing but organizational readiness remains uneven.

Despite these contributions, several limitations should be acknowledged. First, the cross-sectional design limits the ability to establish causal relationships among the variables. Second, the use of self-reported data may introduce perceptual bias, although statistical tests suggest that common method bias is not a major concern. Third, the study focuses on industrial companies in West Java, which may limit the generalizability of the findings to other sectors or regions with different levels of digital maturity. Fourth, the model includes only HR agility as a mediating variable, while other mechanisms such as digital readiness, leadership support, or employee trust in AI may also influence the relationship.

Future research is encouraged to adopt longitudinal designs to better capture causal dynamics and temporal changes in AI-driven HR transformation. Expanding the research context across sectors and countries would enhance generalizability, while incorporating additional mediating and moderating variables could provide a more comprehensive understanding of how AI-driven HRM influences employee and organizational outcomes.

6. Limitations and Future Research

This study has several limitations that should be acknowledged. First, the use of a cross-sectional design restricts the ability to draw strong causal inferences, as the relationships among AI-driven HRM, HR agility, and employee performance were examined at a single point in time. Second, the study relied on self-reported data, which may be subject to perceptual bias and common method variance, despite the procedural and statistical controls applied. Third, the sample was limited to employees of industrial companies in West Java, Indonesia; therefore, the findings may not be fully generalizable to other sectors, organizational settings, or national contexts with different levels of digital maturity. Fourth, this study focused only on HR agility as a mediating variable, while other organizational and behavioral mechanisms may also shape the relationship between AI-driven HRM and employee performance.

Future research is encouraged to address these limitations by adopting longitudinal designs to better capture causal dynamics and changes over time in AI-driven HR transformation. Mixed-method or multi-source data collection approaches could also provide deeper insights and reduce reliance on perceptual measures alone. In addition, future studies may expand the research scope by including other sectors, comparing regions or countries, and examining additional mediating or moderating variables such as digital readiness, leadership support, employee trust in AI, organizational learning, and innovation climate. Such efforts would contribute to a more comprehensive understanding of the conditions under which AI-driven HRM can generate sustainable employee and organizational outcomes.

Acknowledgement
The authors would like to express their sincere appreciation to the participating employees and industrial companies in West Java for their cooperation and valuable contributions to this study. The authors also acknowledge the support of their respective institutions in facilitating the completion of this research.

Declaration of AI and AI-assisted technologies in the writing process
During the preparation of this work, the author(s) used ChatGPT by OpenAI in order to assist with language refinement, academic phrasing, and manuscript organization. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

Reference

Arslan, A., Golgeci, I., Khan, Z., Al-Tabbaa, O., & Hurmelinna-Laukkanen, P. (2022). Artificial intelligence-driven innovation in industrial firms: The role of knowledge sourcing and firm capabilities. *Technovation, 114*, 102420. https://doi.org/10.1016/j.technovation.2021.102420

Bondarouk, T., & Brewster, C. (2016). Conceptualising the future of HRM and technology research. *The International Journal of Human Resource Management, 27*(21), 2652–2671. https://doi.org/10.1080/09585192.2016.1232296

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55

Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence—Challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management, 33*(6), 1065–1097. https://doi.org/10.1080/09585192.2022.2035161

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Thrassou, A. (2021). The impact of artificial intelligence on organizational effectiveness: The role of human resource management. *The International Journal of Human Resource Management, 32*(19), 4183–4210. https://doi.org/10.1080/09585192.2020.1871393

Doz, Y. L., & Kosonen, M. (2010). Embedding strategic agility: A leadership agenda for accelerating business model renewal. *Long Range Planning, 43*(2–3), 370–382. https://doi.org/10.1016/j.lrp.2009.07.006

Felipe, C. M., Roldán, J. L., & Leal-Rodríguez, A. L. (2017). Impact of organizational culture values on organizational agility. *Sustainability, 9*(12), 2354. https://doi.org/10.3390/su9122354

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes: An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Johnson, R. D., Lukaszewski, K. M., & Stone, D. L. (2020). The evolution of the field of human resource information systems: Co-evolution of technology and HR processes. *Human Resource Management Review, 30*(4), 100718. https://doi.org/10.1016/j.hrmr.2019.100718

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Khin, S., & Ho, T. C. F. (2019). Digital technology, digital capability and organizational performance. *International Journal of Innovation Science, 11*(2), 177–195. https://doi.org/10.1108/IJIS-08-2018-0083

Koopmans, L., Bernaards, C. M., Hildebrandt, V. H., van Buuren, S., van der Beek, A. J., & de Vet, H. C. W. (2014). Improving the individual work performance questionnaire using rasch analysis. *Journal of Applied Measurement, 15*(2), 160–175.

Lengnick-Hall, C. A., Beck, T. E., & Lengnick-Hall, M. L. (2011). Developing a capacity for organizational resilience through strategic human resource management. *Human Resource Management Review, 21*(3), 243–255. https://doi.org/10.1016/j.hrmr.2010.07.001

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review, 32*(2), 100795. https://doi.org/10.1016/j.hrmr.2020.100795

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *The International Journal of Human Resource Management, 28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699

Meijerink, J., Bondarouk, T., & Lepak, D. P. (2021). Digital HRM: A new stage of e-HRM and the role of human resource management in digital transformation. *Journal of Management Studies, 58*(5), 1310–1338. https://doi.org/10.1111/joms.12681

Minbaeva, D. (2021). Disrupted HR? Human resource management in the digital age. *Human Resource Management Journal, 31*(1), 1–8. https://doi.org/10.1111/1748-8583.12313

Muduli, A. (2016). Exploring the facilitators and mediators of workforce agility: An empirical study. *Management Research Review, 39*(12), 1567–1586. https://doi.org/10.1108/MRR-10-2015-0236

Pan, S. L., Cui, M., Qian, J., & Li, M. (2022). Digital transformation and organizational agility: The mediating role of strategic flexibility. *Management Decision, 60*(13), 1–18. https://doi.org/10.1108/MD-09-2021-1259

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0184

Sherehiy, B., & Karwowski, W. (2014). The relationship between work organization and workforce agility in small manufacturing enterprises. *International Journal of Industrial Ergonomics, 44*(3), 466–473. https://doi.org/10.1016/j.ergon.2013.11.002

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. *Human Resource Management Review, 25*(2), 216–231. https://doi.org/10.1016/j.hrmr.2015.01.002

Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management, 34*(3), 345–365. https://doi.org/10.1177/2397002220921131

Tallon, P. P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizational agility: Insights from a mediation model. *MIS Quarterly, 35*(2), 463–486. https://doi.org/10.2307/23044052

Teece, D. J., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review, 58*(4), 13–35. https://doi.org/10.1525/cmr.2016.58.4.13

Ulrich, D., & Dulebohn, J. H. (2015). Are we there yet? What's next for HR? *Human Resource Management, 54*(2), 187–204. https://doi.org/10.1002/hrm.21609

Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. *Strategic HR Review, 17*(5), 255–258. https://doi.org/10.1108/SHR-07-2018-0051

Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly, 45*(3), 1557–1580. https://doi.org/10.25300/MISQ/2021/15435

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management, 33*(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C.-E. (2020). Influence of artificial intelligence on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wiblen, S., Marler, J. H., & Boudreau, J. W. (2024). Human resource analytics and the changing nature of HR decision-making. *Human Resource Management Journal, 34*(1), 45–63. https://doi.org/10.1111/1748-8583.12501

Zang, Y., Ye, X., Wang, M., & Arar, K. (2023). Artificial intelligence adoption and employee outcomes: A systematic review and future research agenda. *Technological Forecasting and Social Change, 196*, 122833. https://doi.org/10.1016/j.techfore.2023.122833