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Artificial Intelligence Adoption and Human Resource Agility: Examining the Mediating Role of Employee Adaptability in Enhancing Organizational Performance

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A B S T R A C T

Artificial intelligence (AI) has moved from an experimental technology to a core component of contemporary business operations. Machine learning, predictive analytics, natural language processing, and generative models are now embedded in production planning, logistics, customer service, financial analysis, and talent management. This study examines how artificial intelligence (AI) adoption shapes human resource (HR) agility and organizational performance, and whether employee adaptability mediates these relationships. A quantitative explanatory design was applied using a questionnaire completed by 210 employees of seven AI-implementing plantation, agribusiness, logistics, and technology startup organizations in North Sumatra. The sample size followed Hair et al.'s guideline of five to ten respondents per indicator, and the data were analyzed using PLS-SEM. AI adoption significantly improves employee adaptability, HR agility, and organizational performance. Employee adaptability predicts HR agility and performance, and HR agility enhances performance. Employee adaptability partially mediates the effect of AI adoption, including a serial path through HR agility. The model explains 51.2% of the variance in performance.

Keyword: AI Adoption, Employee Adaptability, HR Agility, Organizational Performance,

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INTRODUCTION

Artificial intelligence (AI) has moved from an experimental technology to a core component of contemporary business operations. Machine learning, predictive analytics, natural language processing, and generative models are now embedded in production planning, logistics, customer service, financial analysis, and talent management (Brynjolfsson & McAfee, 2017; Davenport & Mittal, 2023). Systematic reviews show that AI increasingly shapes how organizations recruit, deploy, develop, and evaluate people, and that its effects reach beyond efficiency to the way work itself is organized (Budhwar et al., 2022; Pereira et al., 2023; Vrontis et al., 2022). The public release of generative AI tools has accelerated this shift, because employees at every level can now use AI directly in their daily

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tasks rather than only through specialized systems controlled by the information technology department (Dwivedi et al., 2023).

Despite this momentum, the performance gains from AI are not automatic. A growing body of research argues that the value of AI depends on the organizational capabilities that surround the technology, especially the human capabilities that allow people to learn, adjust, and collaborate with intelligent systems (Chowdhury et al., 2023; Enholm et al., 2022; Prikshat et al., 2023). Bankins et al. (2024) emphasize that AI operates simultaneously at the individual, team, and organizational levels, so its consequences cannot be understood by examining technology features alone. Mikalef et al. (2022) similarly warn that organizations which focus narrowly on technical deployment may overlook the social and ethical conditions that determine whether AI creates sustainable value. In short, adopting AI is a necessary but insufficient condition for improved performance.

Two human-resource concepts are particularly relevant to this problem. The first is human resource (HR) agility, defined as the capacity of an organization's people-related systems, policies, and practices to sense environmental change and to reconfigure skills, roles, and work arrangements quickly and at low cost (Dessler, 2020; Noe et al., 2017). The second is employee adaptability, the willingness and ability of individual employees to modify their behavior, learn new skills, and manage uncertainty when tasks, tools, and work environments change (Robbins & Judge, 2019). The literature suggests that AI can strengthen HR agility through faster decision making, people analytics, and more flexible talent allocation (Malik et al., 2022; Basu et al., 2023), but also that the realization of this potential rests on employees who are able and willing to adapt to AI-supported work (Cheng et al., 2023; Kong et al., 2023). Yet few empirical studies position employee adaptability as the mechanism that translates AI adoption into HR agility and, ultimately, organizational performance.

This gap is especially relevant for emerging economies, where AI adoption is uneven and the workforce is highly heterogeneous in age, education, and digital experience. Indonesia is one such setting, and North Sumatra provides a particularly instructive case. The province hosts large plantation and agribusiness groups, port and logistics operators, and a growing number of technology startups. Based on preliminary observation and industry mapping, seven organizations across these sectors have implemented AI-related technologies in their business operations: PTPN IV PalmCo, Musim Mas Group, PT Wilmar Nabati Indonesia, PT Socfin Indonesia (Socfindo), PT Pelindo Solusi Digital (ILCS), Superles (PT Daya Cerdas Bangsa), and Rekafin. These organizations differ in size, ownership, and digital maturity, yet all of them ask their employees to work alongside AI-supported systems, such as predictive analytics for operations, digital logistics platforms, automated service channels, and data-driven financial or learning applications. Existing Indonesian evidence indicates that AI can improve employee performance and work engagement when supported by appropriate leadership (Wijayati et

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al., 2022), but the mechanism that links AI adoption to agile HR systems and firm-level outcomes in the plantation, agribusiness, logistics, and startup sectors has received little empirical attention.

Against this background, the present study addresses the following research questions. First, does AI adoption influence employee adaptability, HR agility, and organizational performance? Second, do employee adaptability and HR agility influence organizational performance? Third, does employee adaptability mediate the relationship between AI adoption and HR agility, and between AI adoption and organizational performance? Accordingly, the objectives are to (1) estimate the direct effects of AI adoption on employee adaptability, HR agility, and organizational performance; (2) estimate the effects of employee adaptability and HR agility on organizational performance; and (3) test the mediating role of employee adaptability, including a serial mediation path through HR agility, among employees of the seven organizations studied.

The study contributes in three ways. Theoretically, it integrates the dynamic capabilities view with a human-centered account of AI adoption by showing how an individual-level capability, employee adaptability, links technology adoption to an organization-level capability, HR agility. Empirically, it provides evidence from a multi-sector sample in North Sumatra, a region that is underrepresented in AI and HRM research. Practically, it offers organizational leaders and HR practitioners a basis for sequencing AI investment with adaptability-building initiatives such as training, job redesign, and change communication.

RESEARCH METHOD

This study employs a quantitative, explanatory (causal) research design with a cross-sectional survey. The design is appropriate because the aim is to test hypothesized relationships among latent constructs measured through respondents' perceptions (Sekaran & Bougie, 2019; Sugiyono, 2019). Data were gathered with a structured, self-administered questionnaire and analyzed using partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected because the research model is relatively complex, includes a mediating variable and a serial mediation path, aims at prediction as well as explanation, and does not require strict normality assumptions (Hair et al., 2022; Sarstedt et al., 2022).

The population comprises all employees working in companies in North Sumatra that have implemented AI technology in their business operations. Based on preliminary observation and industry mapping across the plantation, agribusiness, logistics, and technology startup sectors, seven organizations were identified as study objects, as summarized in Table 1. Within each organization, respondents were required to meet three criteria: (a) having worked for at least one year, (b) using AI-enabled systems or being directly affected by them in their regular tasks, and (c) being willing to

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participate voluntarily.

Table 1. Organizations studied and sample allocation

Organization	Sector	Sample (n)	Share (%)
PTPN IV PalmCo	Plantation	52	24.8
Musim Mas Group	Agribusiness	40	19.0
PT Wilmar Nabati Indonesia	Agribusiness	36	17.1
PT Socfin Indonesia (Socfindo)	Plantation	30	14.3
PT Pelindo Solusi Digital (ILCS)	Logistics / digital	24	11.4
Superles (PT Daya Cerdas Bangsa)	Technology startup	16	7.6
Rekafin	Technology startup	12	5.7
Total		**210**	**100.0**

Source: Preliminary observation and authors' data (2026)

The sample size was determined following Hair et al. (2019), who recommend a ratio of five to ten respondents for each indicator in the model, and consistent with the guidance for PLS-SEM given by Hair et al. (2022). The research instrument contains 32 reflective indicators (eight for each of the four constructs). The minimum and recommended sample sizes are therefore calculated as in Equation (1).

$$(5 \times 32) \leq n \leq (10 \times 32) \;\rightarrow\; 160 \leq n \leq 320 \quad (1)$$

A target of 210 respondents was adopted, which lies within this range and exceeds the minimum of 160. Respondents were selected with purposive sampling using the criteria above, and the quota for each organization was allocated proportionally to the estimated size of its AI-exposed workforce, producing the distribution shown in Table 1. In total, 230 questionnaires were distributed between September and October 2026, 218 were returned (response rate 94.8%), and 210 were usable after eight responses were removed because of incomplete answers or straight-lining patterns (usable rate 91.3%).

Primary data were collected through a questionnaire distributed in printed form and through an online form, with coordination from HR or administrative units in each organization. Each construct was measured by eight reflective indicators on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The indicators were adapted from prior studies and from established textbooks and were contextualized to the operating conditions of the seven organizations, as shown in Table 2. A pre-test with 20 employees who were not part of the final sample was used to improve wording and clarity. Respondents were informed of the academic purpose, anonymity, and voluntary nature of participation, and no personally identifying information was collected.

Data were analyzed with SmartPLS following the two-stage procedure recommended by Hair et al. (2022). The first stage evaluates the reflective measurement model: indicator reliability (outer loadings of at least 0.70, with loadings of 0.60–0.70 retained when composite reliability and AVE are

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adequate), internal consistency reliability (Cronbach's alpha, rho_A, and composite reliability between 0.70 and 0.95), convergent validity (average variance extracted, AVE, of at least 0.50), and discriminant validity using the heterotrait–monotrait ratio (HTMT below 0.85). The second stage evaluates the structural model: collinearity (inner variance inflation factor below 3), the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and the significance of path coefficients using bootstrapping with 5,000 subsamples and a two-tailed test at the 5% level (Hair et al., 2021, 2022). Model fit was additionally assessed through the standardized root mean square residual (SRMR).

The structural relationships are represented by Equations (2) to (4), where γ and β denote path coefficients and ζ denotes the structural residual.

$$EA = \gamma_1 AIA + \zeta_1 \quad (2)$$

$$HRA = \gamma_2 AIA + \beta_1 EA + \zeta_2 \quad (3)$$

$$OP = \gamma_3 AIA + \beta_2 EA + \beta_3 HRA + \zeta_3 \quad (4)$$

Indirect effects were estimated as the product of the relevant path coefficients and tested with bootstrapped confidence intervals. Following the mediation taxonomy in Hair et al. (2022), a significant indirect effect combined with a significant direct effect of the same sign indicates complementary (partial) mediation, whereas a significant indirect effect with a non-significant direct effect indicates full (indirect-only) mediation. Common method variance was addressed procedurally through anonymity, neutral item wording, and random ordering of items, and statistically by examining inner VIF values, where all values below 3.3 indicate that collinearity and common method bias are not a serious concern (Hair et al., 2022).

RESULTS AND DISCUSSION

RESULTS

Respondent Profile

The final sample consists of 210 employees from the seven organizations. Table 3 summarizes the demographic profile. Male employees account for 56.2% of respondents and female employees for 43.8%. The largest age group is 31–40 years (41.4%), followed by respondents aged 30 or younger (30.5%), which indicates a workforce that is relatively young and therefore likely to be familiar with digital tools. More than half of respondents hold a bachelor's degree (56.2%), and 76.7% have worked for three years or more, which suggests that most respondents have enough experience to evaluate the changes that accompany AI adoption in their organizations.

Table 3. Respondent profile (n = 210)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	118	56.2
	Female	92	43.8

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Characteristic	Category	Frequency	Percentage (%)
Age	≤ 30 years	64	30.5
	31–40 years	87	41.4
	41–50 years	43	20.5
	> 50 years	16	7.6
Education	Senior high / vocational	38	18.1
	Diploma	33	15.7
	Bachelor	118	56.2
	Master	21	10.0
Tenure	< 3 years	49	23.3
	3–5 years	71	33.8
	6–10 years	55	26.2
	> 10 years	35	16.7

Source: Primary data processed (2026)

Descriptive Statistics

Descriptive statistics for the four constructs are presented in Table 4. Using class intervals for a five-point scale (3.41–4.20 = high and 4.21–5.00 = very high), all four constructs fall in the high category. Employee adaptability has the highest mean among the independent constructs (M = 4.03), which indicates that respondents generally perceive themselves as able to adjust to changes in tools and work methods. Organizational performance records the highest overall mean (M = 4.06), while AI adoption has the lowest (M = 3.94), suggesting that the depth of AI integration still has room to grow in several organizations.

Table 4. Descriptive statistics of research variables

Variable	Items	Mean	SD	Category
AI adoption (AIA)	8	3.94	0.61	High
Employee adaptability (EA)	8	4.03	0.58	High
HR agility (HRA)	8	3.98	0.60	High
Organizational performance (OP)	8	4.06	0.57	High

Source: Primary data processed (2026)

Table 5 breaks the mean scores down by organization. The logistics and digital organization (PT Pelindo Solusi Digital) and the two technology startups (Superles and Rekafin) report the highest scores for AI adoption and adaptability, with several means above 4.10, which is consistent with their digital-native or digital-service orientation. The plantation companies (PTPN IV PalmCo and Socfindo) report the lowest means, although still in the high category. This pattern is plausible because plantation operations combine field-based work, a larger and more dispersed workforce, and a longer history of established routines, so that AI-related change reaches employees more gradually. The agribusiness processors (Musim Mas Group and PT Wilmar Nabati Indonesia) occupy an intermediate position.

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Table 5. Mean scores by organization

Organization	AIA	EA	HRA	OP
PTPN IV PalmCo	3.78	3.92	3.85	3.96
Musim Mas Group	4.02	4.08	4.03	4.12
PT Wilmar Nabati Indonesia	3.95	4.01	3.97	4.06
PT Socfin Indonesia (Socfindo)	3.81	3.94	3.88	3.98
PT Pelindo Solusi Digital (ILCS)	4.10	4.15	4.12	4.14
Superles (PT Daya Cerdas Bangsa)	4.12	4.22	4.18	4.17
Rekafin	4.08	4.20	4.15	4.13

Source: Primary data processed (2026)

Measurement Model Evaluation

The measurement model was evaluated before the structural model. As shown in Table 6, all 32 outer loadings exceed 0.70, ranging from 0.702 to 0.851, so no indicator was removed. Cronbach's alpha ranges from 0.903 to 0.918, rho_A from 0.908 to 0.923, and composite reliability from 0.921 to 0.933, all above the 0.70 threshold and below the 0.95 level that would indicate redundancy. AVE values range from 0.595 to 0.636, exceeding the 0.50 criterion, which confirms convergent validity (Hair et al., 2022).

Table 6. Reliability and convergent validity

Construct	Items	Loadings	α	rho_A	CR	AVE
AI adoption (AIA)	8	0.718–0.842	0.912	0.918	0.928	0.616
Employee adaptability (EA)	8	0.702–0.834	0.903	0.908	0.921	0.595
HR agility (HRA)	8	0.714–0.851	0.915	0.920	0.930	0.626
Organizational performance (OP)	8	0.725–0.846	0.918	0.923	0.933	0.636

Source: SmartPLS output, processed (2026)

Discriminant validity was assessed with the HTMT ratio. Table 7 shows that all HTMT values are between 0.603 and 0.781, below the conservative threshold of 0.85, so each construct is empirically distinct from the others. The highest value is observed between employee adaptability and HR agility (0.781), which is theoretically sensible because both capture adaptive capacity at different levels, but it remains clearly below the cut-off. Together, these results indicate that the measurement model is reliable and valid.

Table 7. Discriminant validity (HTMT)

Construct	AIA	EA	HRA	OP
AI adoption (AIA)	–			
Employee adaptability (EA)	0.712	–		
HR agility (HRA)	0.668	0.781	–	
Organizational performance (OP)	0.603	0.694	0.752	–

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Source: SmartPLS output, processed (2026)

Structural Model Evaluation

Collinearity was checked before interpreting path coefficients. The inner VIF values range from 1.00 to 1.84, far below the threshold of 3, so collinearity is not a concern. The coefficient of determination indicates that AI adoption explains 31.6% of the variance in employee adaptability (R^2 = 0.316; adjusted R^2 = 0.313). AI adoption and employee adaptability together explain 41.5% of the variance in HR agility (R^2 = 0.415; adjusted R^2 = 0.409), and the three antecedents jointly explain 51.2% of the variance in organizational performance (R^2 = 0.512; adjusted R^2 = 0.505). These values are moderate to substantial for behavioral research. Predictive relevance is supported by Q^2 values greater than zero for all endogenous constructs (EA = 0.298; HRA = 0.389; OP = 0.471), and the SRMR of 0.052 is below the 0.08 guideline, indicating acceptable model fit.

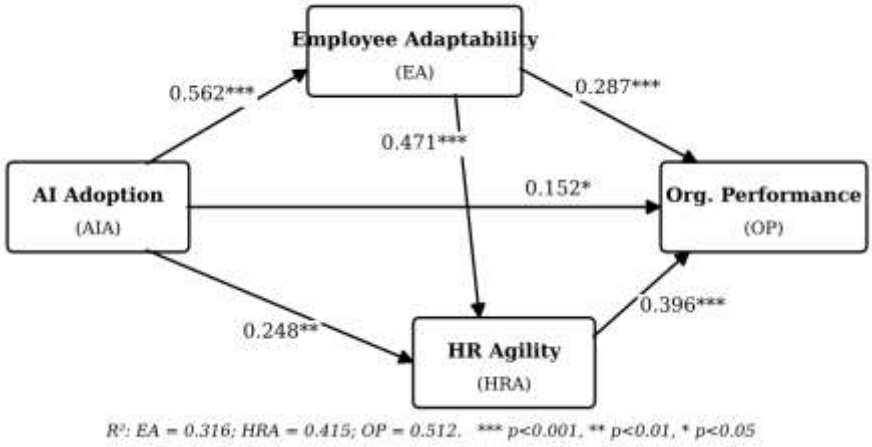

Figure 2. Structural model with standardized path coefficients

Source: SmartPLS output, processed (2026)

Hypothesis Testing

Table 8 reports the bootstrapping results for the direct effects. All six direct paths are positive and statistically significant. AI adoption has the strongest effect on employee adaptability (β = 0.562, t = 9.84, p < 0.001, f^2 = 0.462, a large effect), supporting H1. AI adoption also has a positive effect on HR agility (β = 0.248, t = 3.41, p = 0.001, f^2 = 0.072), supporting H2, although the effect size is small. Employee adaptability has a strong effect on HR agility (β = 0.471, t = 6.52, p < 0.001, f^2 = 0.259), supporting H3. HR agility positively influences organizational performance (β = 0.396, t = 5.87, p < 0.001, f^2 = 0.188), supporting H4. The direct effect of AI adoption on organizational performance is positive but the weakest in the model (β = 0.152, t = 2.18, p = 0.029, f^2 = 0.030), supporting H5, and employee adaptability has a significant effect on organizational performance (β = 0.287, t = 3.96, p < 0.001, f^2 = 0.092), supporting H6.

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Table 8. Direct effects (bootstrapping, 5,000 subsamples)

Path	β	SD	t	p	f^2	Decision
H1: AIA → EA	0.562	0.057	9.84	< 0.001	0.462	Supported
H2: AIA → HRA	0.248	0.073	3.41	0.001	0.072	Supported
H3: EA → HRA	0.471	0.072	6.52	< 0.001	0.259	Supported
H4: HRA → OP	0.396	0.068	5.87	< 0.001	0.188	Supported
H5: AIA → OP	0.152	0.070	2.18	0.029	0.030	Supported
H6: EA → OP	0.287	0.072	3.96	< 0.001	0.092	Supported

Source: SmartPLS output, processed (2026)

Mediation Analysis

Table 9 presents the indirect effects. The specific indirect effect of AI adoption on HR agility through employee adaptability is significant (β = 0.265, t = 5.72, p < 0.001). Because the direct effect of AI adoption on HR agility is also significant and has the same sign, employee adaptability acts as a complementary (partial) mediator, and H7 is supported. The indirect effect of AI adoption on organizational performance through employee adaptability is likewise significant (β = 0.161, t = 3.54, p < 0.001), and the direct effect remains significant, so H8 is supported with complementary partial mediation. The serial path AI adoption → employee adaptability → HR agility → organizational performance is significant (β = 0.105, t = 4.17, p < 0.001), which supports H9. In addition, the path through HR agility alone is significant (β = 0.098, t = 2.84, p = 0.005). The total indirect effect of AI adoption on organizational performance is 0.364, which is more than twice the direct effect (0.152), and the total effect is 0.516. Hence, roughly 70.5% of the total effect of AI adoption on organizational performance operates through the human and HR mechanisms examined here.

Table 9. Indirect effects and mediation

Indirect path	β	SD	t	p	Mediation
H7: AIA → EA → HRA	0.265	0.046	5.72	< 0.001	Partial
H8: AIA → EA → OP	0.161	0.046	3.54	< 0.001	Partial
AIA → HRA → OP	0.098	0.035	2.84	0.005	Partial
H9: AIA → EA → HRA → OP	0.105	0.025	4.17	< 0.001	Serial
Total indirect effect on OP	0.364				
Total effect AIA → OP	0.516				

Source: SmartPLS output, processed (2026)

DISCUSSION

AI Adoption and Employee Adaptability

The finding that AI adoption has a strong positive effect on employee adaptability (H1) is consistent with research showing that organizational AI adoption can stimulate proactive, learning-oriented behavior when employees appraise AI as a challenge rather than a threat (Cheng et al., 2023). It also aligns with Kong et al. (2023), who report that positive beliefs about AI are associated with

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employee–AI collaboration and sustainable careers. In the seven organizations studied, AI adoption is accompanied by a visible expectation that employees learn new systems, interpret data outputs, and adjust workflows. Such a context makes adaptation a daily requirement rather than an optional skill. The large effect size (f^2 = 0.462) suggests that the work context created by AI is the single most important driver of adaptability among the variables in this model.

This result also resonates with evidence that AI can function as a learning aid. Noy and Zhang (2023) and Brynjolfsson et al. (2025) show that AI assistance shortens learning curves, especially for less experienced workers. In the present setting, respondents with shorter tenure and younger respondents are well represented, and this may help explain why the association is strong. At the same time, the descriptive differences between organizations indicate that adaptability is highest in organizations with greater digital maturity, such as Superles, Rekafin, and PT Pelindo Solusi Digital, and somewhat lower in the plantation firms. Employees in plantation operations may need more structured training and peer support because AI tools are introduced into established, field-based routines, a point that echoes the importance of training and role clarity in the job demands–resources perspective.

AI Adoption and HR Agility

The positive but modest direct effect of AI adoption on HR agility (H2) is in line with studies showing that AI-enabled HR practices can raise the speed and flexibility of HR processes (Malik et al., 2022; Basu et al., 2023; Vrontis et al., 2022). Digital platforms and analytics help HR units sense workforce needs, shorten recruitment and administrative cycles, and match skills with tasks. However, the small effect size (f^2 = 0.072) and the large indirect effect through adaptability (β = 0.265) show that technology alone does not make HR systems agile. This supports the argument of Chowdhury et al. (2023) that value from AI in human resource management emerges from the combination of technological infrastructure and human capabilities, and the view of Prikshat et al. (2023) that the consequences of AI-augmented HRM depend on how it is assimilated at multiple levels.

For the organizations studied, the result implies that investments in data platforms or automated HR services will deliver faster talent redeployment, training, and policy response only if employees are prepared to use them and to change roles when required. Responsible implementation also matters: concerns about bias, transparency, and employee data in AI-supported HR decisions can erode trust if not addressed (Chen, 2023; Rodgers et al., 2023; Tursunbayeva et al., 2022).

Employee Adaptability, HR Agility, and Organizational Performance

Employee adaptability has a strong effect on HR agility (H3), which supports the argument that agile HR systems are built on adaptive people (Noe et al., 2017; Fenwick et al., 2024). When employees

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are open to learning, willing to change roles, and comfortable collaborating with AI-supported systems, HR units can reallocate talent, update competencies, and implement policy changes with less resistance. This is particularly relevant for plantation and agribusiness firms that operate across multiple estates, mills, and business units, where redeployment and reskilling require cooperation from large and diverse workforces. It is equally relevant for startups such as Superles and Rekafin, where role boundaries shift quickly as products evolve.

HR agility, in turn, positively influences organizational performance (H4), consistent with research linking agility and resilience to innovation and competitiveness in dynamic environments (Do et al., 2022; Troise et al., 2022). The effect size ($f^2 = 0.188$) is larger than that of the direct AI effect, which indicates that how quickly an organization can mobilize its people is a stronger performance driver than technology exposure alone. The direct effect of employee adaptability on performance (H6) also remains significant, in line with evidence that adaptive employees sustain productivity during technological change and exploit AI tools more fully (Cheng et al., 2023; Brynjolfsson et al., 2025; Kong et al., 2023).

Direct Effect of AI Adoption on Performance

The direct effect of AI adoption on organizational performance (H5) is positive but the smallest in the structural model. This pattern is consistent with the business value literature, which finds that AI contributes to performance mainly through complementary organizational resources and capabilities rather than through technology in isolation (Enholm et al., 2022; Jorzik et al., 2024). It also supports the observation from Indonesian evidence that the benefits of AI for employee performance depend on supporting conditions such as change leadership (Wijayati et al., 2022). In practical terms, the result cautions against evaluating AI projects only by their direct technical outputs, because a large part of the performance return appears indirectly through employee and HR system changes.

The Mediating Role of Employee Adaptability

The central contribution of this study is the evidence that employee adaptability is a significant mediator (H7, H8) and, together with HR agility, forms a serial mediation chain (H9). The indirect effects account for most of the total effect of AI adoption on organizational performance, which implies that the human response to AI is the main channel through which adoption translates into results. This finding is consistent with the multilevel view of AI in organizations (Bankins et al., 2024), with the systematic evidence that AI affects workplace outcomes through multiple processes (Pereira et al., 2023), and with the caution that responsible and human-centered implementation is a precondition for sustainable value (Mikalef et al., 2022). Theoretically, the results extend the dynamic capabilities view by showing that an individual-level adaptive capability is a micro-foundation of an organization-level

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HR capability.

Implications

Several managerial implications follow. First, leaders of PTPN IV PalmCo, Socfindo, Musim Mas Group, and PT Wilmar Nabati Indonesia should pair technology roll-out with structured adaptability programs, such as role-based AI literacy training, supervisor coaching, peer learning in estates and mills, and clear communication on how AI changes tasks and career paths. Second, PT Pelindo Solusi Digital should use its relatively high digital maturity to build internal communities of practice and cross-functional rotations that convert adaptability into HR agility, particularly in the way logistics and port-service teams are staffed. Third, Superles and Rekafin, as technology startups with high adaptability, should formalize HR processes, such as skills inventories and data-based workforce planning, so that their natural flexibility becomes a repeatable organizational capability. Fourth, all organizations should establish transparent governance for AI in people decisions to maintain trust (Papagiannidis et al., 2023; Rodgers et al., 2023). Finally, policy makers and industry associations in North Sumatra can support upskilling initiatives, including vocational and university partnerships, to prepare the regional workforce for AI-enabled operations.

Limitations and Future Research

This study has limitations that suggest directions for future research. The cross-sectional design limits causal inference, and longitudinal or time-lagged designs would better capture how adaptability develops after AI roll-out. All constructs were measured by self-reported perceptions from the same respondents, which, despite procedural remedies, leaves some risk of common method bias; future studies could combine employee data with managerial or objective performance indicators. The sample covers seven organizations in North Sumatra, so generalization to other regions or sectors should be made carefully, and multi-group analysis across sectors or organizations would show whether the structural relationships differ between plantation, agribusiness, logistics, and startup contexts. Future work could also examine moderators such as change leadership, AI literacy, job insecurity, and organizational support, and could differentiate between types of AI, for example analytical, automation-oriented, and generative applications.

CONCLUSION

This study examined how AI adoption influences HR agility and organizational performance and tested the mediating role of employee adaptability among employees of seven AI-implementing organizations in North Sumatra. The results indicate that AI adoption significantly increases employee adaptability, HR agility, and organizational performance, and that employee adaptability and HR agility

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both contribute to organizational performance. Employee adaptability partially mediates the relationship between AI adoption and HR agility as well as the relationship between AI adoption and organizational performance, and a serial path through adaptability and HR agility is also significant. The structural model explains a substantial share of the variance in organizational performance, and the indirect effects represent the larger part of the total effect of AI adoption. These findings show that technology adoption is most valuable when it is accompanied by the development of employees' adaptive capabilities and agile HR systems.

Based on these conclusions, organizations are advised to treat AI adoption as a people-centered change program. Management should integrate training, job redesign, supportive supervision, and transparent communication into AI projects; HR departments should invest in analytics, flexible staffing, and skill-development systems that capitalize on employees' adaptability; and each organization should tailor its approach to its own digital maturity, with plantation and agribusiness firms emphasizing field-level capability building and logistics and startup firms emphasizing formalization of agile HR practices. Future researchers are encouraged to apply longitudinal and multi-source designs and to extend the model with moderators such as change leadership and AI literacy.

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