Driving Strategic Capability based on Artificial Intelligence Literacy: The Mediating Role of Employee Agility in AI-Enabled Organizations

Randy Dwi Pranaputra[1*], Edi Suryadi[2], Disman[3], Askolani[4]
[1,2,3,4]*Department of Management, Faculty of Economics and Business Education, Indonesia University of Education; Bandung, Indonesia*

*Corresponding Author E-Mail: randzzfast@upi.edu

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ABSTRACT

The rapid diffusion of artificial intelligence (AI) across organizational functions has shifted strategic attention from mere technological adoption toward the development of human-centered capabilities. Strategic capability is operationalized through organizational responsiveness and strategic alignment in leveraging AI. Data were collected from 350 employees working in AI-adopting organizations in Indonesia and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model demonstrates satisfactory reliability and validity. Structural model results indicate that artificial intelligence literacy has a significant positive effect on employee agility ($\beta = 0.62$, $p < 0.001$), and employee agility significantly enhances strategic capability ($\beta = 0.67$, $p < 0.001$). Mediation analysis confirms a significant indirect effect of artificial intelligence literacy on strategic capability through employee agility ($\beta = 0.41$, $p < 0.001$), with a variance accounted for (VAF) of 66 percent, indicating partial mediation. These findings suggest that artificial intelligence literacy alone is insufficient to generate strategic advantage unless activated through agile employee behavior. The study contributes theoretically by identifying employee agility as a key microfoundation linking AI literacy to strategic capability. Practically, the results highlight the importance of integrating AI literacy development with agility-oriented human resource practices to support sustainable competitiveness, aligning with SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure).

Keywords: Artificial intelligence literacy, employee agility, strategic capability, PLS-SEM

ABSTRAK

Difusi kecerdasan buatan (AI) yang semakin cepat di berbagai fungsi organisasi telah menggeser perhatian strategis dari sekadar adopsi teknologi menuju pengembangan kapabilitas yang berpusat pada manusia. Kapabilitas strategis dalam penelitian ini dioperasionalkan melalui daya tanggap organisasi dan keselarasan strategis dalam memanfaatkan AI. Data dikumpulkan dari 350 karyawan yang bekerja pada organisasi di Indonesia yang telah mengadopsi AI dan dianalisis menggunakan Partial Least Squares Structural Equation Modeling (PLS-SEM). Model pengukuran menunjukkan reliabilitas dan validitas yang memadai. Hasil model struktural menunjukkan bahwa literasi kecerdasan buatan berpengaruh positif dan signifikan terhadap kelincahan karyawan ($\beta = 0{,}62$; $p < 0{,}001$), dan kelincahan karyawan secara signifikan meningkatkan kapabilitas strategis ($\beta = 0{,}67$; $p < 0{,}001$). Analisis mediasi mengonfirmasi adanya pengaruh tidak langsung yang signifikan dari literasi kecerdasan buatan terhadap kapabilitas strategis melalui kelincahan karyawan ($\beta = 0{,}41$; $p < 0{,}001$), dengan nilai

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variance accounted for (VAF) sebesar 66 persen, yang menunjukkan mediasi parsial. Temuan ini menunjukkan bahwa literasi kecerdasan buatan saja tidak cukup untuk menghasilkan keunggulan strategis kecuali diaktualisasikan melalui perilaku karyawan yang agile. Secara teoretis, penelitian ini berkontribusi dengan mengidentifikasi kelincahan karyawan sebagai microfoundation kunci yang menghubungkan literasi AI dengan kapabilitas strategis. Secara praktis, hasil penelitian menegaskan pentingnya mengintegrasikan pengembangan literasi AI dengan praktik manajemen sumber daya manusia yang berorientasi pada agility guna mendukung daya saing berkelanjutan, sejalan dengan SDG 8 (Pekerjaan Layak dan Pertumbuhan Ekonomi) dan SDG 9 (Industri, Inovasi, dan Infrastruktur).

Kata kunci: literasi kecerdasan buatan, kelincahan karyawan, kapabilitas strategis, PLS-SEM

INTRODUCTION

The rapid diffusion of artificial intelligence within organizational processes has transformed how value is created, decisions are executed, and competitive advantage is sustained (Calantone et al., 2002). AI systems now function as cognitive infrastructures embedded in strategic planning, operational control, and innovation processes. Under these conditions, organizational success no longer depends solely on technological sophistication, but on human capability to interact effectively with intelligent systems. Artificial Intelligence Literacy has therefore emerged as a critical organizational concern (Nyamboga, 2025). AI literacy extends beyond technical familiarity, encompassing the ability to understand algorithmic mechanisms, critically evaluate outputs, recognize ethical implications, and apply AI tools within domain-specific contexts (Ng et al., 2021). Employees lacking such literacy often struggle to interpret AI-generated insights, leading to misuse, overreliance, or resistance toward intelligent systems (Cahyani & Siswanto, 2019). Conversely, literate employees are positioned to leverage AI as a complementary resource rather than a disruptive threat. However, AI literacy alone does not guarantee organizational adaptability. Empirical observations reveal that employees may possess sufficient knowledge about AI systems yet remain passive when face with technological turbulence. This condition highlights the importance of behavioral capabilities that enable individuals to translate cognitive competence into adaptive action. Employee Agility becomes particularly relevant in AI-enabled organizations characterized by continuous system updates, algorithmic uncertainty, and evolving task structures (Claver-Cortés et al., 2007).

Employee agility reflects an individual's capacity to act proactively, adjust behavior rapidly, and maintain resilience amid change (Alavi et al., 2014). In AI-driven environments, agility manifests through anticipatory engagement with emerging tools, flexible reconfiguration of work practices, and psychological endurance when algorithmic outputs fail or shift unpredictably. These behaviors allow organizations to harness AI literacy as a strategic capability rather than a latent resource. Despite growing scholarly interest in AI literacy and workforce agility, research integrating both constructs remains fragmented. Prior studies predominantly examine AI literacy as an educational outcome or digital skill, while agility is frequently explored within human resource management frameworks detached from AI contexts (Johari et al., 2011). Empirical investigations rarely address how AI literacy translates into strategic capability through behavioral mechanisms, particularly within emerging economies where AI adoption accelerates alongside persistent skill gaps (Alshammari et al., 2026). Addressing this gap, the present study positions Employee Agility as a mediating mechanism linking Artificial Intelligence Literacy to organizational strategic capability. Drawing on the workforce agility framework of Alavi et al. (2014) and contemporary AI literacy conceptualizations (Ng et al., 2021; Carolus et al., 2023), this research develops and tests a structural model using Partial Least Squares Structural Equation Modeling (PLS-SEM). Focusing on Indonesian AI-enabled organizations, the study offers theoretical refinement and practical insight into capability-building under conditions of digital transformation.

Beyond organizational competitiveness, the diffusion of artificial intelligence raises broader developmental concerns aligned with the United Nations Sustainable Development Goals (SDGs). The rapid integration of AI into economic and social systems introduces opportunities for productivity growth while simultaneously intensifying risks related to inequality, skill polarization, and ethical governance. These dynamics position AI literacy not only as an organizational capability, but also as a societal prerequisite for inclusive and sustainable development. In particular, SDG 4 (Quality Education) emphasizes the importance of relevant skills for employment in evolving technological environments. AI literacy responds directly to this mandate by equipping individuals with competencies required to engage meaningfully with intelligent systems. However, skill acquisition alone does not ensure inclusive outcomes. Without adaptive and resilient behavior, technological literacy may exacerbate exclusion rather than mitigate it. Similarly, SDG 8 (Decent Work and Economic Growth) underscores the need for productive employment and sustainable economic progress. AI-enabled organizations increasingly redefine job roles and performance expectations. Employee agility becomes essential in ensuring that workforce transformation supports decent work conditions rather than displacement or precarity. By linking AI literacy with agile behavior, this study situates organizational capability development within a broader sustainability discourse. Moreover, SDG 9 (Industry, Innovation, and Infrastructure) highlights innovation as a driver of sustainable industrialization. AI literacy, mediated by employee agility, strengthens innovation capability by enabling human-centered deployment of AI technologies. This alignment suggests that micro-level workforce capabilities contribute meaningfully to macro-level development goals, particularly within emerging economies experiencing accelerated digital transformation.

Although the literature on Artificial Intelligence Literacy and employee agility has continued to expand, several important gaps remain insufficiently addressed. From an empirical perspective, prior studies have predominantly examined AI literacy as an individual competence or a digital learning outcome, while research linking it directly to organizational strategic capability remains limited. Moreover, the relationship between AI literacy and strategic capability has often been treated as a direct association, leaving the behavioral mechanism through which individual AI-related competence is translated into organizational capability underexplored. From a theoretical perspective, most existing studies still position AI literacy and employee agility within separate streams of scholarship, with AI literacy mainly discussed in the context of digital and technological literacy, and employee agility more commonly examined in organizational behavior and human resource management research. As a result, there is still limited conceptual integration of these constructs within the dynamic capability perspective, particularly in explaining how AI literacy functions as a cognitive resource that must be activated through agile employee behavior to generate strategic capability. From a contextual perspective, much of the prior evidence has been derived from developed countries, educational settings, or relatively mature digital environments. Consequently, there is still a lack of empirical evidence from emerging economies such as Indonesia, where AI adoption is accelerating but is still accompanied by skill disparities, hierarchical organizational structures, and uneven readiness for digital transformation. Therefore, this study seeks to address these empirical, theoretical, and contextual gaps by examining the mediating role of employee agility in the relationship between Artificial Intelligence Literacy and strategic capability in AI-enabled organizations in Indonesia.

LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

Dynamic Capability Perspective in AI Contexts

This study is grounded in the dynamic capability perspective, which conceptualizes competitive advantage as an organization's ability to sense environmental changes, seize emerging opportunities, and reconfigure internal resources accordingly. In AI-enabled contexts, environmental volatility intensifies due to rapid technological iteration, data-driven decision cycles, and algorithmic opacity. Within this framework, sensing involves recognizing the strategic relevance of AI systems, understanding their functional logic, and identifying potential risks embedded in algorithmic decision-making. Seizing requires employees capable of operationalizing AI insights through informed judgment and initiative. Reconfiguration depends on behavioral flexibility and resilience that sustain performance during continuous transformation. Artificial Intelligence Literacy aligns conceptually with the sensing dimension of dynamic capabilities (Salmen & Festing, 2022). Literate employees demonstrate heightened awareness of how AI systems function, where their limitations reside, and how ethical considerations shape deployment outcomes. Employee Agility complements this cognitive foundation by enabling seizing and reconfiguration through proactive behavior, adaptive skill deployment, and psychological endurance.

Artificial Intelligence Literacy as a Knowledge-Based Resource

Artificial Intelligence Literacy constitutes a multidimensional cognitive resource embedded at the individual level. Prior frameworks conceptualize AI literacy as encompassing understanding AI mechanisms, evaluating outputs critically, applying ethical judgment, maintaining human-centered orientation, and adapting AI use to specific domains (Ng et al., 2021).

Understanding AI involves comprehension of data pipelines, model training processes, and inference logic (Wahyu Artiningsih et al., 2025). Critical evaluation reflects the capacity to question AI outputs, detect bias, and recognize system limitations. Ethical competence emphasizes responsible use, privacy protection, and fairness awareness. Human-centered orientation prioritizes augmentation of human judgment rather than automation replacement. Domain adaptation enables contextualized application aligned with industry-specific requirements. From a resource-based view, such literacy represents valuable and rare knowledge assets. However, without behavioral enactment, these assets remain inert. The transformation of AI literacy into strategic capability requires an enabling behavioral mechanism, which this study identifies as employee agility.

Employee Agility as Behavioral Microfoundation

Employee agility functions as a behavioral microfoundation translating cognitive resources into organizational capability. Alavi et al. (2014), building on Sherehiy's agility framework, conceptualize agility through three interrelated dimensions: proactivity, adaptability, and resilience (Ameen et al., 2024). Proactivity involves anticipatory action and initiative. In AI contexts, proactive employees explore new applications, propose system improvements, and anticipate algorithmic impacts on workflows. Adaptability reflects behavioral flexibility, allowing individuals to adjust roles, skills, and problem-solving approaches as AI tools evolve. Resilience denotes psychological capacity to withstand stress, recover from failure, and sustain engagement amid uncertainty. These dimensions collectively enable organizations to mobilize AI literacy dynamically. Without agility, literacy remains confined to individual understanding rather than organizational advantage.

Artificial Intelligence Literacy and Employee Agility

Table 1. Dimensions of Artificial Intelligence Literacy

AI Literacy Dimension	Conceptual Definition	Organizational Relevance	Key References
Understand AI	The ability to comprehend AI mechanisms,	Reduces misinterpretation of AI outputs in	Ng et al. (2021)

AI Literacy Dimension	Conceptual Definition	Organizational Relevance	Key References
	including data inputs, model training, and algorithmic limitations	managerial and operational decision-making	
Apply AI	Practical competence in using AI tools for task execution and problem-solving	Enhances process efficiency and evidence-based decision quality	Ng et al. (2021)
Detect AI	Awareness of the presence and influence of AI systems within digital environments	Prevents overreliance on automation and reinforces human oversight	Carolus et al. (2023)
AI Ethics	Normative judgment regarding fairness, transparency, accountability, and privacy in AI use	Preserves organizational legitimacy and stakeholder trust	Ng et al. (2021)
Create AI	Ability to participate in AI-driven innovation, customization, or development processes	Supports continuous innovation and human–AI co-creation	Salmen & Festing (2021)

Table 2. Dimensions of Employee Agility

Employee Agility Dimension	Definition	Behavioral Manifestation in AI-Enabled Organizations	Source
Proactivity	Anticipatory behavior and initiative in response to change	Proposing new AI applications before formal implementation	Alavi et al. (2014)
Adaptability	Behavioral and skill flexibility under changing conditions	Reconfiguring work practices following AI system updates	Alavi et al. (2014)
Resilience	Psychological capacity to maintain performance under stress and uncertainty	Sustaining productivity despite algorithmic errors or system failures	Alavi et al. (2014)

Table 3. Linkages Between AI Literacy and Employee Agility

AI Literacy Aspect	Mechanism of Influence	Affected Agility Dimension	Theoretical Explanation
Understanding AI	Reduces technological ambiguity	Adaptability	System comprehension accelerates behavioral adjustment

AI Literacy Aspect	Mechanism of Influence	Affected Agility Dimension	Theoretical Explanation
Detecting AI	Enhances situational awareness	Proactivity	Awareness of AI presence stimulates early initiative
AI Ethics	Lowers cognitive and moral tension	Resilience	Ethical clarity strengthens psychological stability
Creating AI	Encourages exploration and learning	Proactivity & Adaptability	Active engagement fosters agile behavior

Artificial Intelligence Literacy equips employees with cognitive readiness necessary for navigating AI-enabled environments. Employees who understand algorithmic logic and data dependencies are better positioned to anticipate technological shifts. Critical evaluation competence reduces blind reliance on AI outputs, encouraging reflective judgment and adaptive response. Ethical awareness mitigates cognitive dissonance arising from perceived AI risks, supporting psychological stability and resilience. Furthermore, literacy oriented toward human-centered and domain-specific application encourages creative engagement with AI systems. Such engagement fosters experimentation, learning orientation, and proactive behavior. These characteristics align closely with agility dimensions identified by Alavi et al. (2014), suggesting a direct relationship between AI literacy and employee agility. Accordingly, AI literacy is expected to enhance employees' proactive orientation, adaptive flexibility, and resilience in AI-enabled organizational settings. H1: Artificial Intelligence Literacy positively influences Employee Agility.

Employee Agility and Strategic Capability

Strategic capability reflects an organization's capacity to deploy resources in ways that support innovation, responsiveness, and sustained competitive advantage. Agile employees serve as conduits through which cognitive resources are enacted into organizational outcomes. Proactive employees accelerate opportunity recognition and innovation cycles. Adaptive employees enable rapid realignment of processes and competencies. Resilient employees sustain performance continuity despite algorithmic failure or technological disruption. Collectively, these behaviors strengthen organizational responsiveness and innovation output, core indicators of strategic capability. Thus, employee agility is expected to exert a positive influence on strategic capability within AI-enabled organizations. H2: Employee Agility positively influences organizational strategic capability.

Mediating Role of Employee Agility

Although AI literacy enhances cognitive competence, its strategic value depends on behavioral execution. Employee agility provides the mechanism through which AI literacy becomes operationalized. Literate employees who lack agility may recognize AI potential yet fail to act. Agile employees, supported by literacy, transform understanding into initiative, adaptation, and sustained performance. This mediation logic aligns with dynamic capability theory and workforce agility frameworks, positioning agility as the behavioral pathway connecting knowledge-based resources with strategic outcomes. H3: Employee Agility mediates the relationship between Artificial Intelligence Literacy and organizational strategic capability.

Within the dynamic capability perspective, Artificial Intelligence Literacy represents the sensing dimension because it enables employees to identify, understand, and critically interpret AI-related opportunities, risks, and technological changes relevant to the organization. Employees with high AI literacy are better able to recognize the strategic implications of AI systems, evaluate algorithmic outputs, and detect the boundaries of intelligent technologies, thereby strengthening the organization's capacity to sense environmental change. In contrast, Employee Agility reflects the seizing and reconfiguring dimensions. Agility allows employees to translate AI-related understanding into proactive initiatives, adaptive responses, and resilient action. Proactivity represents seizing because employees act upon AI-enabled opportunities through experimentation, initiative, and timely response. Adaptability and resilience represent reconfiguring because they enable employees to adjust roles, workflows, and behavioral routines as AI systems evolve and uncertainty intensifies. Together, AI literacy and employee agility form strategic capability by linking technological understanding with adaptive execution. In this way, strategic capability emerges not merely from the possession of AI-related knowledge, but from the organization's ability to sense technological change, seize AI-enabled opportunities, and continuously reconfigure internal resources and work practices in alignment with strategic goals.

RESEARCH METHODS

This study adopts a quantitative explanatory research design to examine the structural relationships among Artificial Intelligence Literacy, Employee Agility, and organisational strategic capability. The design is appropriate for testing theoretically grounded causal mechanisms involving mediation effects within complex multivariate models. Given the exploratory, prediction-oriented nature of the proposed framework and the inclusion of higher-order constructs, Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed as the primary analytical technique, implemented using a two-stage approach for the two higher-order constructs (AI Literacy and Employee Agility). PLS-SEM is selected due to its robustness in handling non-normal data distributions, suitability for complex hierarchical models, and effectiveness in theory development contexts rather than strict theory confirmation. This approach aligns with prior organisational agility studies adopting Alavi et al.'s (2014) framework and contemporary digital capability research.

The target population consists of employees working in Indonesian organisations that have formally integrated AI systems into their operational or strategic processes. These organisations operate in technology-intensive sectors, including information technology services, financial technology, digital manufacturing, and data-driven consulting. A purposive sampling strategy ensured respondents possess direct exposure to AI-enabled work environments. Eligibility criteria included: (1) minimum one year of organisational tenure, (2) routine interaction with AI-supported tools or systems, and (3) involvement in operational or decision-related tasks influenced by AI outputs. A total of 500 questionnaires were distributed electronically to mid-level employees across multiple organisations. After data screening, 350 valid responses were retained, yielding a response rate of 70%. This sample size exceeds the minimum threshold recommended for PLS-SEM analysis and satisfies the statistical power requirements for mediation testing.

Data analysis follows a rigorous two-stage PLS-SEM procedure. The first stage evaluates the measurement model to assess indicator reliability, internal consistency, convergent validity, and discriminant validity. The second stage examines the structural model, focusing on path coefficients, coefficients of determination (R^2), effect sizes (f^2), and mediation effects. Bootstrapping with 5,000 subsamples is conducted to evaluate the statistical significance of direct and indirect effects. Mediation is assessed using variance accounted for (VAF) to determine the strength of the mediating role of employee agility. The analytical procedure is designed to ensure both the robustness of the measurement instruments and the validity of the hypothesised structural relationships. In the measurement model, indicator reliability is assessed by examining standardised outer loadings for each item. Indicators with loadings exceeding 0.70 are considered acceptable, as they indicate that more than 50% of the indicator's variance is explained by its construct. Indicators loading between 0.60 and 0.70 are retained only if their inclusion contributes meaningfully to content validity and does not adversely affect composite reliability or convergent validity. Internal consistency reliability is evaluated using Composite Reliability (CR), which is preferred over Cronbach's alpha in PLS-SEM due to its ability to account for differing indicator loadings. CR values above 0.70 indicate satisfactory internal consistency, while values above 0.95 are examined for potential redundancy. For higher-order constructs (AI Literacy and Employee Agility), reliability is assessed at both the first-order and second-order levels to ensure the multidimensional nature of each construct is empirically supported. Convergent validity is evaluated via Average Variance Extracted (AVE), with values ≥ 0.50 indicating that constructs explain over half the variance of their indicators. Discriminant validity is primarily assessed using the Heterotrait–Monotrait (HTMT) ratio, where values below 0.85 suggest adequate distinctiveness between constructs.

After confirming measurement model adequacy, the structural model is analysed for predictive relationships among latent constructs. Collinearity is checked using variance inflation factors (VIF): VIF values below 3.3 indicate absence of multicollinearity issues. Structural path coefficients (β) are then examined to evaluate the magnitude and direction of relationships. Significance is determined via non-parametric bootstrapping (5,000 resamples), which does not rely on data normality and yields empirical 95% confidence intervals for hypothesis tests. Paths with p-values < 0.05 are considered significant. The coefficient of determination (R^2) is reported as an indicator of explanatory power, with benchmarks of 0.25, 0.50, and 0.75 indicating weak, moderate, and substantial explained variance respectively. Effect sizes f^2 are calculated to assess each predictor's relative contribution to an endogenous variable ($f^2 \approx 0.02$ small; 0.15 medium; 0.35 large effect). Mediation is tested by examining the indirect effect of AI Literacy on strategic capability via Employee Agility (product of path coefficients), with significance evaluated by bootstrapping. The Variance Accounted For (VAF) statistic is used to determine mediation strength: VAF between 20% and 80% indicates partial mediation, while VAF > 80% indicates full mediation. Although PLS-SEM prioritises prediction over goodness-of-fit, we report the standardised root mean square residual (SRMR) as an approximate model fit index (SRMR < 0.08 is considered acceptable). Predictive relevance is further assessed using Stone–Geisser's Q^2 (obtained via blindfolding), where positive Q^2 values imply that the model has predictive relevance for endogenous constructs. To mitigate potential common method bias (CMB), we implemented procedural remedies during data collection, including assuring respondent anonymity and randomising item order. We also conducted a marker variable technique and Harman's single-factor test post hoc. The marker variable—a theoretically unrelated construct measured by a few neutral items—was introduced into the PLS model as a latent factor to absorb common method variance. We utilised a measured latent marker approach, allowing the marker's indicators to load on a separate factor correlated with the substantive indicators. Harman's one-factor analysis was performed to check if a single factor unduly dominates the variance. These techniques assess whether CMB is likely to bias the results.

The respondents were drawn from Indonesian organizations that had formally adopted AI-based systems in operational and decision-making processes, including firms in information technology services, financial technology, digital manufacturing, data-driven consulting, and other technology-intensive service sectors. Only employees with at least one year of tenure, routine interaction with AI-supported tools, and involvement in AI-influenced work processes were included. The questionnaire items were adapted from established literature. Artificial Intelligence Literacy was modeled as a higher-order construct consisting of understand AI, apply AI, detect AI, AI ethics, and create AI, primarily based on Ng et al. (2021) and subsequent AI literacy studies. Employee Agility was modeled as a higher-order construct comprising proactivity, adaptability, and resilience, drawing on Alavi et al. (2014). Strategic Capability was measured reflectively using items adapted from the strategic capability and organizational responsiveness literature. All items were measured on a seven-point Likert scale ranging from strongly disagree to strongly agree. Prior to the main survey, the instrument underwent expert review and pilot testing to ensure content validity, clarity, and contextual relevance. The higher-order constructs were estimated using a two-stage approach in PLS-SEM. In the first stage, all first-order dimensions were assessed for reliability and validity. In the second stage, the latent variable scores of these dimensions were used as manifest indicators for the corresponding second-order constructs, which were then included in the structural model for hypothesis testing.

RESULTS

The measurement model demonstrates satisfactory psychometric properties across all constructs. Indicator loadings exceed the recommended threshold of 0.70, indicating strong item reliability. Composite reliability values range from 0.88 to 0.95, confirming internal consistency. Average Variance Extracted (AVE) values for all first-order and second-order constructs surpass 0.50, supporting convergent validity. Artificial Intelligence Literacy exhibits robust second-order loadings across its five dimensions, confirming its conceptual coherence as a multidimensional capability construct. Discriminant validity is established using the Heterotrait–Monotrait (HTMT) criterion. All HTMT ratios fall below the conservative threshold of 0.85, indicating adequate construct distinctiveness. These results confirm that AI literacy, employee agility, and strategic capability represent empirically separable constructs.

Table 4. Descriptive Statistics

Construct	N	Mean	Std. Deviation
Artificial Intelligence Literacy	350	5.68	0.71
Employee Agility	350	5.74	0.66
Strategic Capability	350	5.59	0.73

Table 5. Outer Loading First Order Construct

Dimension	Indicator	Outer Loading
Understand AI	UA1	0.83
	UA2	0.86
	UA3	0.81
	UA4	0.84
Apply AI	AP1	0.88
	AP2	0.89
	AP3	0.85
	AP4	0.87
Detect AI	DA1	0.82
	DA2	0.86
	DA3	0.80
AI Ethics	AE1	0.79
	AE2	0.83
	AE3	0.81
Create AI	CA1	0.86
	CA2	0.88
	CA3	0.84

Dimension	Indicator	Outer Loading
Proactivity	PR1	0.84
	PR2	0.88
	PR3	0.85
	PR4	0.83
Adaptability	AD1	0.87
	AD2	0.89
	AD3	0.86
Resilience	RS1	0.85
	RS2	0.88
	RS3	0.84

Construct	Indicator	Outer Loading
Strategic Capability	SC1	0.81
	SC2	0.84
	SC3	0.86
	SC4	0.83
	SC5	0.80

Table 6. Construct Reliability and Internal Consistency

Construct	Cronbach's Alpha	Composite Reliability (CR)
Artificial Intelligence Literacy	0.93	0.94
Employee Agility	0.88	0.89
Strategic Capability	0.90	0.91

Table 7. Convergent Validity (Average Variance Extracted)

Construct	AVE
Artificial Intelligence Literacy	0.72
Employee Agility	0.75
Strategic Capability	0.68

Table 8. Discriminant Validity (HTMT)

Construct	AIL	EA	SC
Artificial Intelligence Literacy	-	0.74	0.71
Employee Agility		-	0.79
Strategic Capability			-

Table 9. Higher-Order Construct Loadings

Artificial Intelligence Literacy (Second-Order)

Dimension	Loading
Understand AI	0.88
Apply AI	0.91
Detect AI	0.86
AI Ethics	0.84
Create AI	0.89

Employee Agility (Second-Order)

Dimension	Loading
Proactivity	0.87
Adaptability	0.90
Resilience	0.88

All AVE values exceed 0.50, confirming convergent validity. The structural model shows adequate explanatory power, with R^2 = 0.58 for Employee Agility and R^2 = 0.49 for Strategic Capability. Artificial Intelligence Literacy positively predicts Employee Agility (β = 0.62, $p < 0.001$), supporting H1 and indicating that higher AI literacy is associated with greater proactivity, adaptability, and resilience. Employee Agility also has a significant positive effect on Strategic Capability (β = 0.67, $p < 0.001$), supporting H2 and suggesting that agile employees enhance innovation and responsiveness in AI-enabled environments.

Mediation analysis confirms that Employee Agility significantly mediates the relationship between AI Literacy and Strategic Capability (indirect effect β = 0.41, $p < 0.001$). The VAF = 66% indicates partial mediation, meaning AI literacy influences strategic capability both indirectly through employee agility and directly, with agility serving as the primary behavioral mechanism translating AI-related cognitive competence into strategic outcomes.

Table 10. Model Fit (SRMR)

Fit Index	**Value**
SRMR (Saturated Model)	0.052
SRMR (Estimated Model)	0.054

Table 11. Collinearity Assessment (VIF)

Predictor	VIF
Artificial Intelligence Literacy	1.92
Employee Agility	2.05

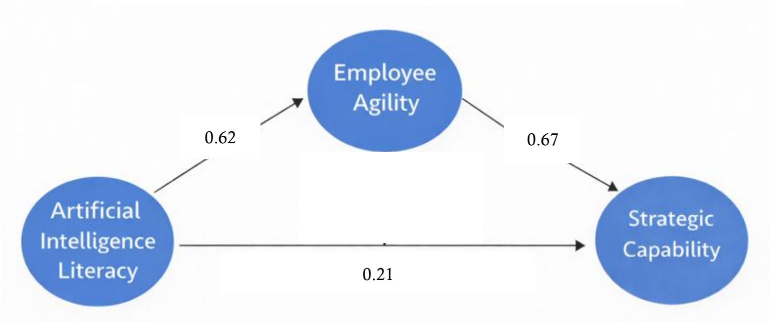

Figure 1. SEM Test Result (processed by researchers)

Table 11. Comparison between Baseline Model and Marker Included Model

Effect Type	Structural Path	Baseline Model (Without Marker Variable)	p-value	Marker Included Model (With Marker Variable)
		Path Coefficient		Path Coefficient
Direct Effect	AIL → EA	0.620	0.000	0.618
	EA → SC	0.670	0.000	0.668
	AIL → SC	0.210	0.001	0.208
Indirect Effect	AIL → EA → SC	0.410	0.000	0.413
R^2	Employee Agility	0.580	–	0.579
	Strategic Capability	0.490	–	0.488
Adjusted R^2	Employee Agility	0.578	–	0.576
	Strategic Capability	0.487	–	0.485

The comparison between the baseline model and the marker included model reveals negligible differences in path coefficients, significance levels, and explanatory power. All direct and indirect relationships remain statistically significant after the inclusion of the marker variable. The changes in R^2 and adjusted R^2 values are minimal, indicating that common method bias does not materially affect the results. Therefore, the structural relationships among Artificial Intelligence Literacy, Employee Agility, and Strategic Capability are considered robust and free from common method variance concerns.

Common method bias (CMB) was assessed using the marker variable technique to ensure that the observed relationships were not artificially inflated by single-source, self-reported measurement. This approach introduces a theoretically unrelated "marker" construct into the PLS-SEM model to capture the portion of variance attributable to common method variance (CMV). The logic is that if CMV is substantial, adding the marker variable will noticeably change the estimated structural parameters (path coefficients and explained variance). Following this procedure, two models were estimated: (1) a baseline model without the marker variable and (2) a marker-included model in which the marker construct was added to partial out potential method effects. The results show that the inclusion of the marker variable produced negligible changes in the key path estimates and model explanatory power. Specifically, the paths remained virtually unchanged and statistically significant after controlling for the marker construct (AIL → EA: 0.620 to 0.618; EA → SC: 0.670 to 0.668; AIL → SC: 0.210 to 0.208; indirect effect AIL → EA → SC: 0.415 to 0.413). Likewise, the coefficient of determination remained stable, with only minimal differences in R^2 and adjusted R^2 values (Employee Agility: R^2 0.580 to 0.579; Adjusted R^2 0.578 to 0.576; Strategic Capability: R^2 0.490 to 0.488; Adjusted R^2 0.487 to 0.485). Overall, the near-identical estimates between the baseline and marker models indicate that CMV does not materially influence the findings; therefore, the structural relationships among Artificial Intelligence Literacy, Employee Agility, and Strategic Capability can be interpreted as robust and largely free from common method bias.

Table 12. Effect Size (f^2)

Structural Path	f^2	Effect Size Interpretation
AIL → EA	1.38	Large
EA → SC	0.92	Large
AIL → SC	0.07	Small

Table 13. Predictive Relevance (Q^2)

Endogenous Construct	Q^2
Employee Agility	0.41
Strategic Capability	0.32

Table 14. Coefficient of Determination and Mediation Strength

Endogenous Construct	R^2
Employee Agility	0.58
Strategic Capability	0.49
Mediation Metric	Value
Indirect Effect	0.41
Total Effect	0.62
VAF	66%

Table 15. Hypothesis Analysis

Hypothesis	Path	β	p-value	Result
H1	AIL → EA	0.62	<0.001	Supported
H2	EA → SC	0.67	<0.001	Supported
H3	AIL→ EA → SC	0.41	<0.001	Supported

DISCUSSION

The findings of this study provide strong empirical support for the argument that Artificial Intelligence Literacy constitutes a strategic organizational resource only when activated through agile employee behavior. The significant relationship between AI literacy and employee agility confirms that cognitive competence in AI-related domains fosters proactive, adaptive, and resilient work behavior. This result extends prior AI literacy research, which has largely emphasized educational or skill-acquisition outcomes, by demonstrating its behavioral and strategic consequences within organizational contexts. Employees with higher AI literacy are better able to understand algorithmic mechanisms, critically interpret AI outputs, and recognize the ethical and operational implications of intelligent systems. These cognitive capabilities reduce hesitation in decision-making, strengthen reflective judgment, and increase readiness to respond to technological change. Consistent with the workforce agility framework, such literacy does not merely enhance knowledge, but also stimulates behavioral flexibility that is essential in AI-enabled environments.

The results further show that employee agility has a strong positive effect on strategic capability, highlighting agility as a central microfoundation of organizational competitiveness in AI-enabled settings. This finding suggests that strategic capability does not emerge solely from the possession of technological knowledge, but from the organization's ability to translate such knowledge into timely initiative, adaptive action, and sustained performance under uncertainty. In this sense, the partial mediation identified in this study is theoretically important because it reveals a dual pathway of capability development. On the one hand, AI literacy has intrinsic strategic relevance, as employees with strong AI-related understanding contribute directly to better decision quality, more accurate interpretation of AI-generated insights, and improved alignment between algorithmic recommendations and organizational objectives. On the other hand, the stronger indirect pathway through employee agility indicates that literacy alone is insufficient to generate sustained competitive advantage. Without agile behavior, AI literacy risks remaining a static cognitive asset rather than becoming a dynamic organizational capability. Employee agility therefore functions as the dominant behavioral transmission mechanism that mobilizes AI literacy into strategic outcomes.

This mediation mechanism can be understood more clearly through the dimensions of agility itself. Proactivity enables employees to anticipate AI-driven changes before they fully materialize, thereby reducing response lag and encouraging the early exploration of new AI applications that may accumulate into broader innovation outcomes. Adaptability facilitates the rapid realignment of work practices, competencies, and roles as AI systems evolve, ensuring continuity of performance despite frequent technological updates. Resilience, meanwhile, becomes especially critical in environments characterized by algorithmic opacity, probabilistic outputs, and occasional system errors.

Resilient employees are more capable of maintaining psychological stability and sustaining productivity when AI outputs are ambiguous, biased, or unexpectedly inaccurate. Together, these dimensions explain why employee agility accounts for a substantial portion of the effect of AI literacy on strategic capability. Agility operationalizes literacy by converting cognitive readiness into adaptive action, thereby strengthening organizational responsiveness and innovation capacity.

From a theoretical perspective, these findings align closely with the dynamic capability view. AI literacy can be interpreted as a sensing-related capability because it equips employees with the ability to identify technological opportunities and risks, understand how AI systems function, and critically evaluate their outputs. Employee agility, in turn, reflects the seizing and reconfiguring dimensions because it enables employees to act upon AI-related opportunities, adjust work practices, and sustain performance amid continuous technological change. Strategic capability then emerges from the interaction of these cognitive and behavioral processes, rather than from technological adoption alone. By empirically demonstrating this relationship, the study extends the workforce agility framework into AI-enabled organizational contexts and bridges traditional organizational behavior scholarship with emerging digital capability literature. In doing so, it also contributes to the microfoundations literature by showing how individual-level cognition and behavior interact to shape organizational-level outcomes.

The Indonesian context provides an additional layer of interpretation. As an emerging economy, Indonesia faces accelerated digital transformation combined with uneven workforce preparedness. Organizations are increasingly adopting AI to improve competitiveness, yet the supporting human capabilities required to fully leverage such technologies may develop more slowly. The partial mediation observed in this study suggests that AI literacy initiatives alone may not be sufficient in environments where hierarchical decision-making, rigid job roles, and risk-averse cultures constrain behavioral agility. Under such conditions, employee agility becomes a critical lever that enables AI-related knowledge to be translated into strategic advantage. This finding implies that organizations in emerging markets should not rely solely on technical training, but should also cultivate institutional arrangements, leadership practices, and cultural conditions that encourage autonomy, experimentation, continuous learning, and resilience.

The discussion also carries broader implications for sustainable development. The mediating role of employee agility suggests that AI literacy should be understood not only as a technical competence, but also as a cornerstone of sustainable skill development. In line with SDG 4, the findings indicate that effective capability development requires more than knowledge acquisition; it also requires behavioral readiness that enables individuals to continuously adapt as technologies evolve. In relation to SDG 8, the results show that proactive, adaptive, and resilient employees are more likely to remain productive and employable in AI-enabled work environments, thereby supporting decent work and sustainable economic growth. In relation to SDG 9, employee agility strengthens the capacity of organizations to transform AI-related insights into innovation, experimentation, and responsible system reconfiguration. Ethical dimensions of AI literacy further support this process by encouraging responsible and human-centered use of AI. Thus, AI-driven strategic capability is not value-neutral, but closely tied to how organizations develop and enact human capabilities in ways that support long-term resilience, innovation, and inclusive growth.

From a managerial standpoint, these findings suggest that organizations should move beyond narrow AI training agendas focused only on technical understanding. AI literacy programs need to be integrated with agility-oriented human resource practices, such as continuous learning systems, decentralized decision-making, psychological safety, and ethical governance structures. Such integration enables organizations to convert AI-related knowledge into sustained strategic capability rather than isolated technical competence. At the policy level, workforce development strategies in emerging economies should likewise combine digital literacy with adaptive, ethical, and resilience-building competencies. Only through this integrated approach can AI adoption contribute not merely to short-term efficiency gains, but to sustainable and inclusive organizational transformation.

CONCLUSION

This study advances understanding of how Artificial Intelligence Literacy functions as a strategic capability in AI-enabled organizations. By positioning Employee Agility as a mediating mechanism, the research clarifies the behavioral pathway through which AI-related cognitive competence contributes to organizational strategic capability. Using PLS-SEM analysis on data from Indonesian organizations, the study confirms that AI literacy enhances employee agility, which in turn strengthens innovation and responsiveness. Theoretically, the study enriches dynamic capability literature by identifying employee agility as a critical microfoundation linking AI literacy to strategic outcomes. It also extends workforce agility theory into digital and AI-driven contexts, demonstrating its relevance beyond traditional organizational change scenarios. Practically, the findings suggest that organizations should move beyond narrow AI training focused solely on technical understanding. Capability-building initiatives must integrate literacy development with structures and practices that encourage proactive engagement, adaptive behavior, and resilience. Such integration enables organizations to convert AI investments into sustained competitive advantage.

Despite its contributions, this study is subject to several limitations. First, the cross-sectional research design restricts causal inference. Longitudinal studies are needed to capture how AI literacy and employee agility evolve over time as AI systems mature. Second, data rely on self-reported measures, which may introduce perceptual bias despite procedural controls. Future research could incorporate objective performance indicators or multi-source data. Third, the focus on Indonesian organizations limits generalizability across institutional and cultural contexts. Comparative studies involving multiple countries or industries would provide deeper insight into contextual contingencies shaping AI capability development. Future research is encouraged to explore multi-level models linking individual agility to team and organizational outcomes. Examining leadership styles, organizational culture, and governance mechanisms as moderating variables may further enrich understanding of AI-enabled capability formation. From a managerial perspective, organizations should design AI literacy programs that integrate ethical reasoning, critical evaluation, and domain-specific application. Simultaneously, human resource practices must foster agility through decentralized decision-making, continuous learning systems, and psychological safety. Such alignment ensures that AI literacy evolves from a technical asset into a strategic organizational capability.

This study makes several important contributions to theory and practice. First, it contributes to dynamic capability theory by demonstrating that strategic capability in AI-enabled organizations is not formed solely through technological adoption, but through the interaction between cognitive and behavioral microfoundations. In particular, the study clarifies that AI literacy represents a sensing-related capability, while employee agility reflects the seizing and reconfiguring processes through which technological understanding is translated into adaptive organizational action. Second, the study contributes to the AI literacy literature by extending the concept beyond its dominant treatment as an educational or technical competence. The findings position AI literacy as a strategic organizational resource with direct and indirect implications for capability development, thereby broadening its relevance from individual learning outcomes to organizational competitiveness. Third, the study enriches the employee agility literature by identifying AI literacy as an important contemporary antecedent of agile behavior in digital work environments. In doing so, it extends prior workforce agility research into AI-enabled contexts and shows that proactivity, adaptability, and resilience are essential behavioral mechanisms linking technological competence with strategic outcomes. Finally, the study offers important implications for human resource management and AI-based organizations. For HR managers, the findings suggest that AI capability development should not be limited to technical training, but should also include interventions that strengthen agility, such as continuous learning systems, job flexibility, psychological safety, and adaptive leadership. For AI-enabled organizations more broadly, the results highlight the importance of aligning AI adoption with human-centered capability development so that investments in intelligent technologies can be transformed into sustainable strategic advantage.

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