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The Impact of AI Integration on Organizational Agility: Mediating Mechanisms of Collaboration and Process Flexibility

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[Abstract]

This study examines how AI integration relates to organizational agility and operational performance through two intermediate organizational mechanisms (collaboration and process flexibility) within an Input–Process–Output (IPO) framework. Extending the IT-agility perspective to the AI context, we use PLS-SEM to analyze survey data from 231 managers in AI-using firms. AI integration is positively associated with both collaboration and process flexibility, and these two mechanisms are, in turn, positively related to organizational agility, which is further associated with operational performance. Both serial paths are statistically significant; however, the total indirect effect is small (0.037), and its practical magnitude should therefore be interpreted with caution. The findings suggest that agility is not an automatic byproduct of AI adoption but emerges when AI integration is accompanied by a substantive reconfiguration of collaboration patterns and process structures. Rather than claiming strong prediction of performance, the study contributes by identifying the intermediate organizational mechanisms through which AI integration is translated into adaptive capability.

▸ **Key words**: AI Integration, Organizational Agility, Collaboration, Process Flexibility, Operational Performance, PLS-SEM

[요 약]

본 연구는 AI 통합이 협업과 프로세스 유연성이라는 두 매개 메커니즘을 통해 조직 민첩성으로 이어지는 과정을 투입-과정-산출 (IPO) 구조로 분석하였다. AI를 활용 중인 기업 관리자 231명 자료에 5,000회 부트스트랩 PLS-SEM을 적용한 결과, AI 통합은 협업(β=0.406, $p<.001$)과 프로세스 유연성(β=0.375, $p<.001$)을 유의하게 높였고, 두 변수는 민첩성에 거의 동등하게 기여하였으며(β=0.245, 0.255), 민첩성은 다시 운영 성과를 유의하게 예측하였다(β=0.190, p=.003). 두 연쇄 매개경로(H6, H7) 모두 95% 신뢰구간이 0을 포함하지 않아 유의하였고, 작은 총 간접효과(0.037)는 단계별 감쇠를 시사한다. 즉 민첩성은 AI 도입의 자동적 산물이 아니라 협업 패턴과 프로세스 구조의 실질적 재편을 필요로 한다. 본 연구는 Sambamurthy 외[1]의 IT 민첩성 프레임워크를 AI 맥락으로 확장하여, AI 통합이 적응적 역량으로 전환되는 조직적 미시 기반을 규명한다.

▸ **주제어**: AI 통합, 조직 민첩성, 협업, 프로세스 유연성, 운영 성과, PLS-SEM

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I. Introduction

1. Contributions of the Study

The IT-agility framework of Sambamurthy et al. [1] did not separately test how the prediction and automation functions distinctive to AI affect collaboration and process structures. To fill this gap, this study empirically examines the intermediate organizational mechanisms through which technological potential is converted into adaptive capability. We show that AI contributes to agility through two qualitatively different routes: coordinating people and information (collaboration) and restructuring work (process flexibility). In doing so, we provide an empirical response to recent calls to identify the intermediate capabilities that connect digital investment with realized value [4]. Accordingly, the primary contribution of this study lies in explaining the organizational mechanisms through which AI integration is translated into adaptive capability rather than in demonstrating a direct performance effect.

II. Theoretical Background and Hypotheses

1. Organizational Agility Theory and AI

Sambamurthy et al. [1] argued that IT promotes agility and competitive action through digital options, and Overby et al. [2] conceptualized agility as the combination of sensing and responding capabilities. Tallon and Pinsonneault [5] empirically demonstrated the mechanism by which IT alignment contributes to agility, and Teece et al. [8] discussed the strategic role of agility from a dynamic capabilities perspective. By providing analytical, predictive, and automation capabilities beyond traditional IT [6],[9], AI can improve both the accuracy of environmental sensing and the speed of response; however, converting technological capability into agility depends on organizational mediation [4].

In this study, AI integration is defined as the degree to which AI-based analytical, predictive, and automation functions are embedded in, and actively used for, day-to-day work processes. This definition deliberately distinguishes AI integration from mere AI adoption (possession of the technology), from general digital transformation (broad digitization of the firm), and from a firm's latent AI capability (resource endowment). It corresponds to the measurement items AIN1–AIN3, which capture cross-process embeddedness and the use of AI analytics in key decision making. In short, what defines AI integration is the organizational embedding of AI in everyday work rather than the mere possession of the technology.

The proposed framework conceptualizes this phenomenon as an Input–Process–Output system in which AI integration (Input) shapes collaboration and process flexibility (Process), which in turn drive agility and operational performance (Output). Collaboration and process flexibility thus serve as the key intermediate organizational mechanisms that translate AI-based information processing into organizational behavior.

2. Collaboration and Process Flexibility

Collaboration refers to interaction spanning interdepartmental information sharing, joint decision making, and integrated problem solving [10]. AI-based collaboration tools can reduce interdepartmental information asymmetry and make collaboration more efficient [7]. Process flexibility is the ability to reconfigure existing work processes quickly in response to environmental change [11]. AI-based automation and optimization tools can support the dynamic adjustment of processes [12].

The three focal constructs are conceptually distinct and operate at different levels. Collaboration is a social coordination mechanism (how people and units align information and decisions); process flexibility is a structural mechanism (how readily work structures can be reconfigured); and organizational agility is an organization-level sensing-and-responding capability that draws on both. Accordingly, AI is theorized to operate on collaboration by reshaping information sharing and joint decision making, and on process flexibility by enabling process reconfiguration and faster response (two theoretically separable pathways rather than a single, undifferentiated effect). The empirical distinctness of the constructs is further supported by the HTMT discriminant-validity results (all ratios < 0.85; see Table 2b).

3. Hypotheses

Each hypothesis follows from the mechanisms described above. Because AI integration reduces information asymmetry and supports joint decision making, it is expected to relate positively to collaboration (H1); because it enables automated process reconfiguration, it is expected to relate positively to process flexibility (H2). As coordination and structural reconfiguration are the enabling routes of sensing and responding, collaboration (H3) and process flexibility (H4) are expected to relate positively to agility, which in turn is expected to relate to operational performance (H5). Together, these links form the two serial paths, H6 and H7.

H1: AI integration is positively associated with collaboration.

H2: AI integration is positively associated with process flexibility.

H3: Collaboration is positively associated with organizational agility.

H4: Process flexibility is positively associated with organizational agility.

H5: Organizational agility is positively associated with operational performance.

H6: The serial path AI integration → collaboration → agility → performance is significant.

H7: The serial path AI integration → process flexibility → agility → performance is significant.

These hypotheses form an Input-Process-Output (IPO) system structure in which AI integration is the input, collaboration and process flexibility are the process, and organizational agility and operational

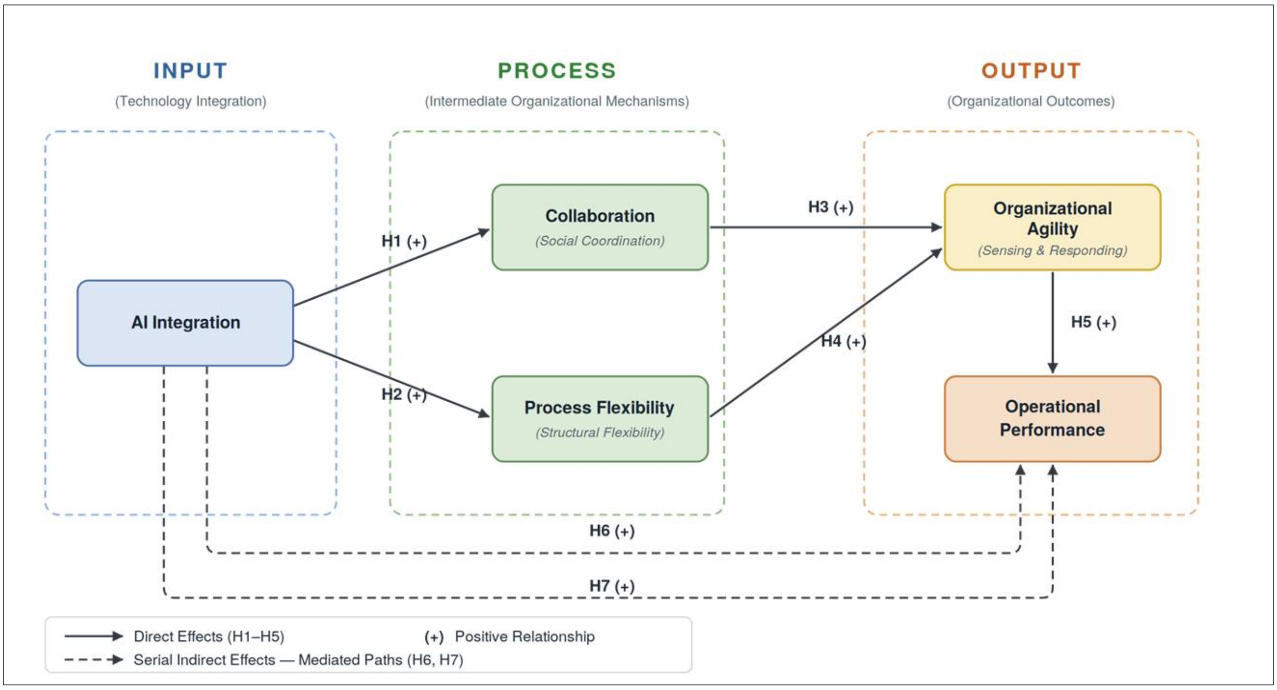

Fig. 1. Research Model (Input-Process-Output)

Note. Solid arrows denote the hypothesized direct paths (H1–H5); dashed arrows denote the two serial indirect paths: H6 (AI integration → collaboration → agility → operational performance) and H7 (AI integration → process flexibility → agility → operational performance). (+) indicates a hypothesized positive relationship.

performance are the output. Fig. 1 labels the Input, Process, and Output blocks and marks the hypothesized paths, distinguishing the two serial mediation routes (H6, H7) as dashed arrows.

III. Research Method

1. Sample and Data Collection

The target population was managers in domestic firms actively using AI in their work. Data were collected in April 2026 through a professional panel-based online survey platform. Purposive sampling was applied to manager-level panelists with experience in AI-based work. Of the 267 questionnaires distributed and collected, 36 careless responses were excluded, yielding a final analytic sample of 231 (valid response rate 86.5%). The 36 responses were excluded according to pre-specified screening criteria: (1) completion time below the minimum threshold, (2) straight-lining (identical responses across a block), (3) failed attention-check items, (4) missing values on key items, and (5) logical inconsistency across reverse-worded items.

The demographic and organizational profile of the respondents is summarized in Table 1.

Respondents were managers with AI-based work experience across diverse functional units (planning, sales, production, R&D, etc.); an analysis of variance (ANOVA) across functional-unit groups showed no significant difference in the means of the main constructs (all $p > .10$).

2. Measurement Instruments

All constructs were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The items were adapted from established prior scales and reworded for the AI-in-the-workplace context, with item selection prioritizing face validity for AI-enabled work. The original English scales were translated into Korean and independently back-translated into English by a native-English bilingual specialist, and the two versions were reconciled to confirm semantic equivalence. The source of each item is reported in Appendix Table A1. AI integration (3 items) assesses the degree of AI embeddedness across work [6]. Collaboration (3 items) assesses interdepartmental cooperation, information sharing, and joint decision making [10]. Process flexibility (3 items) assesses ease of reconfiguration, adaptability, and flexible response [11]. Organizational agility (3 items) assesses environmental response, task reconfiguration, and timely response [1]. Operational performance (3 items) assesses productivity, cost reduction, and project success rate [13]. Industry experience (years) and AI usage frequency (times per week) were included as control variables.

3. Analysis Method

Partial least squares structural equation modeling (PLS-SEM; SmartPLS 4.0 [14]) was

Table 1. Respondent Profile (N = 231)

Attribute	Category	%	Attribute	Category	%
Industry	Manufacturing	28	Managerial level	Junior mgr	41
	IT / Software	24		Middle mgr	44
	Finance / Insurance	14		Senior / Executive	15
	Retail / Distribution	12	Department	Planning / Strategy	21
	Services	13		Sales / Marketing	23
	Other	9		Production / Ops	19
Firm size (emp.)	< 100	22		R&D	18
	100-299	26		IT / Other	19
	300-999	27	AI use duration	< 1 yr	27
	≥ 1000	25		1-2 yr	34
AI use domain	Analytics / forecasting	31		2-3 yr	23
	Content generation	26		≥ 3 yr	16
	Process automation / etc.	43			

adopted, and significance was tested with 5,000 bootstrap resamples. All five constructs are modeled as reflective, since their indicators are interchangeable manifestations of a common latent variable. Mardia's multivariate normality test indicated a significant departure from normality ($p < .01$), which makes the distribution-free PLS-SEM estimator more appropriate than covariance-based SEM for these data. In addition, because the AI-agility mechanism is at a theory-building stage and the model contains a complex serial-mediation structure, the prediction-oriented, exploratory emphasis of PLS-SEM is methodologically suitable for this specific model [15],[16],[17].

IV. Results

1. Measurement Model Evaluation

Outer loadings ranged from 0.728 to 0.881. Cronbach's α ranged from 0.768 to 0.868, composite reliability (CR) from 0.796 to 0.908, and average variance extracted (AVE) from 0.566 to 0.768 [18]. Table 2 reports, at the construct level, the loading range, indicator reliability (the square of each loading), α, CR, and AVE; R^2 for each endogenous construct is reported with the structural results, keeping measurement- and structural-model indicators distinct.

All reflective constructs met the recommended thresholds: Cronbach's α (0.768–0.868) and composite reliability (0.796–0.908) exceeded 0.70, and AVE (0.566–0.768) exceeded 0.50 [18]. Operational performance showed the lowest reliability (α = 0.768, CR = 0.796, AVE = 0.566) but still satisfied all convergent-validity criteria, indicating that OPF1–OPF3 cohere reasonably as a single construct.

2. Structural Model Evaluation

SRMR = 0.071 (meeting the ≤ 0.08 criterion). Blindfolding-based Q^2 values were positive for every endogenous construct (collaboration 0.121, process flexibility 0.098, organizational agility 0.104, and operational performance 0.031), establishing predictive relevance. The maximum variance inflation factor (VIF) was 2.12, below the 3.3 threshold [20]. AI integration was significantly related to both collaboration (β = 0.406, f^2 = 0.197) and process flexibility (β = 0.375, f^2 = 0.165). The model accounted for R^2 = 0.165 (collaboration), 0.141 (process flexibility), 0.160 (organizational agility), and 0.062 (operational performance).

Against Cohen's benchmarks for f^2 (0.02, 0.15, and 0.35 for small, medium, and large effects [21]), the effects of AI integration on the two mediators are at or above the medium threshold, whereas the path from agility to performance (f^2 = 0.037) is

Table 2. Measurement Model Results

Construct	Items	Loadings	Ind. rel.	α	CR	AVE
AI Integration	3	0.869–0.881	0.755–0.776	0.868	0.908	0.768
Collaboration	3	0.788–0.823	0.621–0.677	0.810	0.850	0.654
Process Flexibility	3	0.780–0.821	0.608–0.674	0.827	0.846	0.648
Organizational Agility	3	0.770–0.815	0.593–0.664	0.807	0.838	0.633
Operational Performance	3	0.728–0.792	0.530–0.627	0.768	0.796	0.566

Note. All standardized factor loadings are significant at $p < .001$.

Table 2b. Discriminant Validity – HTMT Matrix

HTMT	AIN	COL	PFX	AGI	OPF
AI Integration	–				
Collaboration	0.46	–			
Process Flexibility	0.44	0.52	–		
Organizational Agility	0.30	0.58	0.81	–	
Operational Performance	0.18	0.22	0.20	0.24	–

Note. All HTMT ratios are below the 0.85 threshold [19].

Table 3. Structural Model Results

	Path	β	95% CI	t	p / f^2	Result
H1	AI Integration → Collaboration	0.406	[0.289, 0.523]	6.811	<.001 / 0.197	Supported
H2	AI Integration → Process Flexibility	0.375	[0.255, 0.495]	6.110	<.001 / 0.165	Supported
H3	Collaboration → Organizational Agility	0.245	[0.120, 0.370]	3.853	<.001 / 0.065	Supported
H4	Process Flexibility → Organizational Agility	0.255	[0.133, 0.377]	4.082	<.001 / 0.070	Supported
H5	Organizational Agility → Operational Perf.	0.190	[0.064, 0.316]	2.961	.003 / 0.037	Supported
c1	Industry experience → Agility (control)	0.041	[-0.086, 0.170]	0.64	.522 / 0.003	n.s.
c2	AI usage frequency → Agility (control)	0.058	[-0.070, 0.185]	0.88	.379 / 0.005	n.s.
c3	Industry experience → Performance (control)	0.033	[-0.094, 0.161]	0.51	.610 / 0.001	n.s.
c4	AI usage frequency → Performance (control)	0.047	[-0.082, 0.174]	0.72	.471 / 0.002	n.s.

Note. R^2 of endogenous constructs: COL = 0.165, PFX = 0.141, AGI = 0.160, OPF = 0.062.

small. Table 3 reports 95% bias-corrected bootstrap confidence intervals for every path, together with the two control variables.

The R^2 of operational performance is only 0.062, meaning that the model explains a very limited portion of the variance in performance. This value is acknowledged as low; accordingly, we refrain from strong practical claims about performance improvement and locate the study's contribution in the identification of the mediating mechanism rather than in the prediction of performance.

We also estimated an alternative model that added the direct paths AI integration → agility, AI integration → performance, and collaboration/process flexibility → performance; each additional direct path was non-significant (all $p > .05$). In this model the direct effect of AI integration on operational performance was small and non-significant ($\beta = 0.031$, $p = .420$), supporting a near-full-mediation rather than a partial-mediation interpretation.

3. Serial Mediation Analysis

As shown in Table 4, in the bootstrap analysis (5,000 resamples, bias-corrected CIs), both serial mediation paths were significant, with 95% CIs that excluded zero. Although statistically significant, the two indirect effects (0.019, 0.018) and the total indirect effect (0.037) are very small in standardized magnitude; statistical significance should therefore be clearly distinguished from practical importance. We interpret this small total indirect effect as a mathematical consequence of multiplying standardized coefficients across successive stages (a×b×c): the product of several coefficients below one is necessarily smaller than any single coefficient in the chain. We therefore treat it as an interpretive observation rather than a formally tested “stepwise attenuation” mechanism.

4. Common Method Bias (CMB) Assessment

Common method bias (CMB) was assessed using four methods in parallel. In Harman's single-factor test, the variance explained by the first factor was 27.1%, well below the 50% threshold [22]. In Kock's [20] full-collinearity VIF assessment, the VIF of all latent variables was at most 2.12, below the 3.3 threshold. Applying the marker-variable technique of Lindell and Whitney [23], we used “general attitude toward technology,” a theoretically unrelated marker, whose correlations with the focal constructs were negligible ($r < 0.05$). After marker-variable adjustment, the key path coefficients were substantively unchanged (e.g., H1: 0.406 → 0.402; H5: 0.190 → 0.187), indicating no material method effect. As ex-ante procedures, we

Table 4. Serial Mediation Analysis (H6, H7)

Path	Effect	95% CI	p	Result
AI → Collaboration → Agility → Performance (H6)	0.019	[0.005, 0.043]	<.001	Supported
AI → Flexibility → Agility → Performance (H7)	0.018	[0.004, 0.036]	<.001	Supported
Total indirect effect	0.037	[0.011, 0.070]	<.001	–
Direct effect AI → Performance (alt. model)	0.031	[-0.049, 0.112]	.420	n.s.

separated the measurement order of the independent and dependent variables, ensured respondent anonymity, and worded items to minimize social-desirability bias. Taken together, these results suggest that common method bias is unlikely to be the sole explanation for the findings; we do not claim that CMB has been fully eliminated.

5. Robustness Checks

In a 10,000-resample bootstrap analysis, the direction and significance of all key paths remained stable. For the non-response bias check, we compared early and late respondents (first vs. last quartile of completion date) using independent-samples t-tests on the main constructs; no significant mean differences were found (all $p > .10$), suggesting non-response bias is not a serious concern. To examine potential endogeneity, we applied the Gaussian copula approach [24]. AI integration was treated as the potentially endogenous regressor; its non-normality (a precondition for the method) was confirmed by a Shapiro-Wilk test ($p < .01$), and the copula term was constructed from the empirical distribution of AI integration and entered alongside the original predictor. The copula term coefficient was non-significant ($\beta = 0.028$, $p = .394$), and the coefficients and significance of the main paths remained consistent with the baseline analysis, indicating a low likelihood of endogeneity bias.

V. Discussion

1. Interpretation of the Key Findings

The coefficients ($\beta = 0.406$ and $\beta = 0.375$) are consistent with the view that AI is associated with agility mainly through collaboration and process structures rather than directly. AI appears to function less as a direct driver of agility than as an enabler of the organizational mechanisms that produce it. Consistent with the non-significant direct paths reported in Section IV.2, this indicates that AI creates organizational value primarily through organizational transformation rather than through direct technological effects. Agility appears to emerge not automatically from AI adoption alone, but when adoption is accompanied by the reconfiguration of collaboration patterns and more flexible process structures [4],[6]. The similar magnitudes of the two paths to agility ($\beta = 0.245$ vs. 0.255) suggest that social coordination and structural flexibility may operate in a complementary manner. These findings therefore suggest that AI should be viewed primarily as an organizational enabler whose value depends on complementary organizational capabilities rather than as an independent driver of organizational performance.

2. Perceptual Measurement and Causality

All variables in this study are based on managers' perceptual assessments, which are widely used in strategic-management and information-systems research [6],[13]. We nonetheless emphasize that perceived operational performance is not equivalent to objective performance, and that same-source, same-time measurement raises the possibility of common-method inflation. Future research that triangulates these findings with objective indicators (such as productivity records, cost data, project completion rates, process cycle time, or customer response time) would strengthen them.

3. Theoretical Contributions

By extending the IT-agility framework of Sambamurthy et al. [1] to the AI context, this study confirms that the two paths of social coordination (collaboration) and structural flexibility (process) relate to agility in a complementary manner. Relative to prior AI-capability research (which links AI to performance largely as a direct resource effect [6],[12]), IT-agility research (which treats IT alignment broadly [5]), and digital-transformation studies (which emphasize firm-level change), our specific contribution is the empirical identification of two intermediate, serially ordered organizational mechanisms through which AI integration is converted into agility. We therefore frame the novelty in these concrete terms, rather than as a broad “among the first” claim. This perspective contributes to the growing literature that emphasizes organizational transformation as the primary pathway through which AI generates sustainable organizational value.

4. Practical Implications

The results offer tentative, rather than prescriptive, suggestions. When adopting AI, firms may wish to foster interdepartmental collaboration alongside technical automation and to build the capability for dynamic process reconfiguration. Because path coefficients alone cannot justify investment priorities, these implications should be read as directions to explore rather than as definitive managerial prescriptions. Given the small indirect effect, when evaluating the returns to AI investment it may also be useful to check, stage by stage, whether each intermediate step (collaboration and process flexibility) is functioning as intended.

VI. Limitations and Future Research

This study has several limitations that qualify its conclusions. First, the cross-sectional design precludes causal inference; longitudinal or experimental designs are needed. Second, the study relies on purposive sampling from an online professional panel and on single-country (Korean) data, which limits representativeness and generalizability. Third, all constructs, including operational performance, are self-reported perceptual measures from a single respondent per firm, raising the risk of common-method bias; perceived performance is not objective performance, and no objective performance data were available. Fourth, operational performance was measured with only three perceptual items and showed the lowest internal consistency among the constructs (Cronbach's α = 0.768); future work should expand the item pool and complement it with objective indicators. Fifth, the explained variance in operational performance is low (R^2 = 0.062); the model should therefore be read as one that clarifies mediating mechanisms rather than one that predicts performance.

Sixth, the sample consists only of managers. Managers were targeted because they can observe organization-level collaboration, processes, and performance and because they influence resource allocation and decisions about continued technology adoption. However, frontline (non-managerial) employees also understand their organizations and may in fact use AI tools more intensively, so their assessments could differ from managers' perceptions. Future research should therefore adopt multi-level, multi-source designs that combine managerial and frontline respondents.

Finally, this study conceptualizes AI use at the functional level without distinguishing specific technology types, and predictive validity could be examined more comprehensively using the full PLSpredict procedure [17]; extensions incorporating moderators such as organizational culture or leadership style would also be valuable. Future studies may further distinguish between generative AI and predictive AI because different AI technologies may influence organizational agility through different organizational mechanisms.

VII. Conclusion

This study examined how AI integration relates to organizational agility through the two mediating paths of collaboration and process flexibility. Using PLS-SEM on data from 231 managers, AI integration was positively associated with collaboration (β = 0.406) and process flexibility (β =

0.375), which in turn related to agility and, serially, to operational performance; both serial paths were significant but small.

Theoretically, the study identifies the intermediate organizational mechanisms (social coordination and structural flexibility) through which AI integration translates into adaptive capability, extending the IT-agility view to AI. Practically, it tentatively suggests that AI adoption may need to be paired with investment in collaboration systems and process-reconfiguration capability. Its main limitations are the cross-sectional, single-source, single-country design, the low reliability and low explained variance of operational performance, and the exclusive use of managerial respondents, each of which points to longitudinal, multi-source, and objectively measured extensions. Overall, the findings suggest that the strategic value of AI lies not in the technology itself but in the organizational mechanisms through which AI-generated information is transformed into coordinated organizational action.

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APPENDIX. Survey Items

Table A1. Measurement Items

Construct	Item	Measurement Item	Source
AI Integration	AIN1	AI is integrated across the organization's work processes.	[6]
	AIN2	AI analytics are used in key decision making.	[6]
	AIN3	AI is embedded in work processes.	[6]
Collaboration	COL1	Interdepartmental cooperation is smooth.	[10]
	COL2	Information sharing is effective.	[10]
	COL3	Joint decision making is active.	[10]
Process Flexibility	PFX1	Work processes are easy to reconfigure.	[11]
	PFX2	Processes adapt quickly to change.	[11]
	PFX3	We respond flexibly to new requirements.	[11]
Organizational Agility	AGI1	We respond flexibly to environmental change.	[1]
	AGI2	We reconfigure tasks quickly.	[1]
	AGI3	We respond to market opportunities in a timely manner.	[1]
Operational Performance	OPF1	Productivity has improved.	[13]
	OPF2	Costs have been reduced.	[13]
	OPF3	The project success rate has increased.	[13]

Note. All items were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).