

Article

How AI Resources Translate into Supply-Chain Efficiency: Parallel Dynamic Capability Mechanisms in Manufacturing SMEs

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Abstract: Artificial intelligence (AI) offers manufacturing small and medium-sized enterprises (SMEs) new opportunities to improve supply-chain operations, but AI resources do not automatically generate operational value. This study examines how three AI resource-capability foundations-AI Infrastructure Flexibility (AIIF), AI Management Capabilities (AIMC), and AI Personnel Expertise Capability (AIPEC)-are translated into Supply-Chain Efficiency (SCE) through three parallel dynamic capability mechanisms: sensing, seizing, and reconfiguring. Survey data from 604 manufacturing SMEs in Zhejiang Province, China, were analyzed using a two-stage partial least squares structural equation modeling (PLS-SEM) approach. All three dynamic capabilities were positively associated with SCE and jointly explained 31.2% of its variance. All nine specific indirect effects were statistically significant, while the total indirect effects for AIIF (.143), AIMC (.145), and AIPEC (.134) were closely grouped. The findings indicate that AI value realization is distributed across multiple complementary capability-conversion channels rather than concentrated in a single dominant pathway. The study contributes by separating upstream AI resource foundations from the organizational mechanisms through which those resources become operationally valuable.

Keywords: artificial intelligence; supply-chain efficiency; AI value realization; dynamic capabilities; parallel mechanisms; manufacturing SMEs; PLS-SEM

1. Introduction

Artificial intelligence is increasingly used in forecasting, supplier evaluation, inventory control, quality monitoring, logistics planning, and decision support. Yet acquiring AI applications or running successful trials does not guarantee better supply-chain outcomes. This problem is especially important for manufacturing SMEs, where limited capital, specialist labor, and managerial slack make unsuccessful digital investment costly [1]. Research on AI and analytics has established links with organizational performance, resilience, and agility, but the processes through which AI-related resources become operationally valuable remain less explicit [2, 3, 4].

This study addresses that resource-conversion problem by integrating the Resource-Based View (RBV) with Dynamic Capabilities Theory (DCT). RBV explains why heterogeneous technological, managerial, and human resources can be strategically valuable [5], while DCT explains how firms repeatedly sense change, seize opportunities, and reconfigure resources in turbulent environments [6]. The model distinguishes three AI resource-capability foundations-AIIF, AIMC, and AIPEC-and treats sensing, seizing, and reconfiguring as separate parallel mechanisms rather than as one aggregate capability or a sequential chain. Supply-Chain Efficiency is the operational outcome, reflected in product quality, service reliability, order accuracy, and delivery timeliness [7].

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The central question is therefore: How are distinct AI resource foundations translated into Supply-Chain Efficiency through sensing, seizing, and reconfiguring capabilities? The study contributes by opening the resource-performance "black box" through nine specific indirect pathways, preserving sensing, seizing, and reconfiguring as separate conversion mechanisms, and assessing whether AI value realization is concentrated in one channel or distributed across several complementary routes. Figure 1 summarizes the analytical logic.

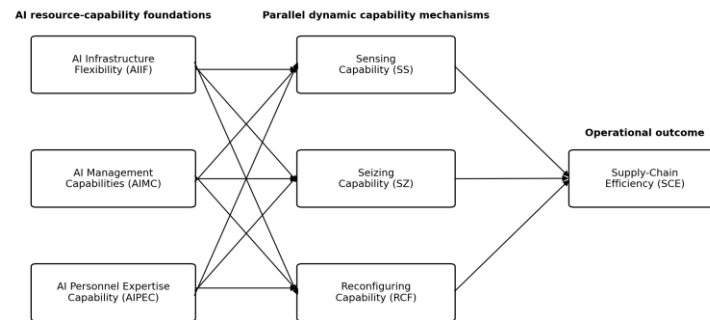


Figure 1. Parallel Dynamic Capability Model Linking AI Resource Foundations to Supply-Chain Efficiency.

2. Theoretical Background and Hypotheses

2.1. AI Resources and the Resource-To-Performance Conversion Problem

From an RBV perspective, AI-related resources can have strategic potential without guaranteeing operational outcomes. This study therefore treats AIIF, AIMC, and AIPEC as three upstream resource foundations representing technological architecture, managerial routines, and personnel expertise, respectively. Keeping these foundations distinct preserves resource heterogeneity, but the purpose of this paper is not to identify an exclusive resource-capability pairing. Instead, the analytical problem is how different AI resource foundations reach a downstream supply-chain outcome through intervening organizational capabilities [5, 8, 9].

DCT supplies this process explanation. Sensing, seizing, and reconfiguring are modeled as parallel conversion mechanisms rather than as a single aggregate capability or a fixed sequence. Sensing converts available resources into timely recognition and interpretation of change; seizing converts recognized issues into committed organizational responses; and reconfiguring converts selected responses into revised routines, systems, and operating arrangements [6, 10, 11]. Modeling the three mechanisms separately makes it possible to examine whether AI-enabled operational value depends on one dominant channel or is distributed across multiple forms of adaptive action.

2.2. Dynamic Capabilities and Supply-Chain Efficiency

Sensing, seizing, and reconfiguring connect adaptive organizational behavior with reliable supply-chain execution in different ways. Sensing reduces the delay between environmental change and organizational awareness, creating time to respond to demand variation, supplier deterioration, quality problems, or logistics disruption. Seizing converts recognized issues into commitments such as reallocating inventory, revising schedules, approving alternative suppliers, or deploying analytical tools. Reconfiguring becomes critical when improvement requires routines, roles, or systems to be redesigned and stabilized rather than handled as one-off decisions. Because these capabilities address distinct but complementary forms of adaptive action, each is expected to contribute positively to Supply-Chain Efficiency [6, 10, 11].

H1a–H1c. Sensing, Seizing, and Reconfiguring Capabilities are positively associated with Supply-Chain Efficiency.

2.3. Parallel Capability-Conversion Pathways from AI Resources to SCE

A specific indirect effect captures the extent to which an upstream AI resource foundation is connected with SCE through a particular dynamic capability. The logic therefore requires two relationships: the resource foundation must support the focal capability, and that capability must in turn contribute to SCE. Because the present study examines conversion rather than specialization, no one-to-one mapping is assumed between a particular AI resource and a single dynamic capability. Each of the three AI resource foundations is therefore evaluated through sensing, seizing, and reconfiguring, producing nine specific indirect pathways. Support across multiple pathways would indicate that AI resources can be translated into operational value through several complementary organizational mechanisms rather than through a single privileged route (As shown in Table 1).

Table 1. Hypothesized Specific Indirect Relationships

AI resource foundation	Through Sensing	Through Seizing	Through Reconfiguring
AIIF	H2a (+)	H3a (+)	H4a (+)
AIMC	H2b (+)	H3b (+)	H4b (+)
AIPEC	H2c (+)	H3c (+)	H4c (+)

3. Methodology

A quantitative cross-sectional survey was conducted among manufacturing SMEs in Zhejiang Province, China. The final analytical sample contained 604 valid questionnaires. Respondents were managers or senior decision makers with knowledge of supply-chain operations and AI-related initiatives. The sample covered all eleven prefecture-level cities in Zhejiang, and all participating organizations were reported as manufacturing firms. The study used purposive sampling complemented by stratification to reach knowledgeable organizational informants.

Measurement items were adapted from established literature and rated on seven-point Likert scales. AIIF, AIMC, and AIPEC were modeled as reflective-formative higher-order constructs. Sensing, seizing, reconfiguring, and SCE were reflective first-order constructs. A two-stage PLS-SEM procedure was applied in SmartPLS 4 following established guidance for hierarchical component models [12, 13]. Stage 1 validated the lower-order reflective constructs and generated latent variable scores; Stage 2 used those scores as formative indicators of the three AI higher-order constructs. Final inference used 10,000 bootstrap subsamples with percentile confidence intervals to evaluate direct and specific indirect effects [14].

Measurement quality was satisfactory. All formative outer VIF values were below 1.45 and all eleven formative weights were positive and significant. The reflective constructs satisfied reliability, convergent validity, and discriminant validity criteria. Because the final model did not include direct paths from AIIF, AIMC, or AIPEC to SCE, the mediation results are interpreted as supported specific indirect effects and are not classified as full or partial mediation [15].

4. Results

All three capability-to-efficiency hypotheses were supported. Sensing had a positive association with SCE ($\beta = .255, p < .001$), as did seizing ($\beta = .227, p < .001$) and reconfiguring ($\beta = .247, p < .001$). Entered simultaneously, the three capabilities explained 31.2% of the variance in SCE. Their coefficients were relatively close, indicating that information interpretation, resource commitment, and operational renewal each contributed unique explanatory value. Because no formal coefficient-difference test was conducted, their numerical ordering should not be interpreted as proof that one capability is statistically stronger than the others.

All nine resource–capability–efficiency indirect effects were positive and statistically significant. The standardized specific indirect effects ranged from .038 to .060, and every 95% bootstrap confidence interval excluded zero. Thus, each AI resource foundation was

connected with SCE through sensing, seizing, and reconfiguring rather than through a single exclusive mechanism. Differences in magnitude were modest and were not formally contrasted; they are therefore treated as descriptive only. Table 2 reports the complete estimates, while Figure 2 visualizes how the indirect effects are distributed across the three parallel capability mechanisms.

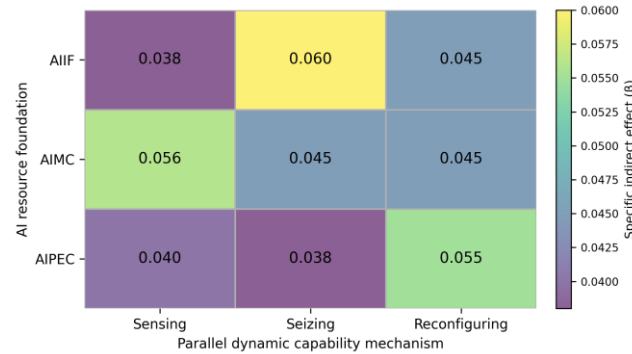


Figure 2. Distribution of Specific Indirect Effects Across Parallel Dynamic Capability Mechanisms

Note. Cell values are standardized specific indirect effects; all nine specific indirect effects are statistically significant.

Table 2. Capability-to-SCE and Specific Indirect Effects

Hypothesis	Path	β	t	p	Decision
H1a	SS $\rightarrow$ SCE	.255	7.491	< .001	Supported
H1b	SZ $\rightarrow$ SCE	.227	6.456	< .001	Supported
H1c	RCF $\rightarrow$ SCE	.247	7.160	< .001	Supported
H2a	AIIF $\rightarrow$ SS $\rightarrow$ SCE	.038	2.853	.004	Supported
H2b	AIMC $\rightarrow$ SS $\rightarrow$ SCE	.056	3.457	< .001	Supported
H2c	AIPEC $\rightarrow$ SS $\rightarrow$ SCE	.040	3.156	.002	Supported
H3a	AIIF $\rightarrow$ SZ $\rightarrow$ SCE	.060	4.476	< .001	Supported
H3b	AIMC $\rightarrow$ SZ $\rightarrow$ SCE	.045	3.505	< .001	Supported
H3c	AIPEC $\rightarrow$ SZ $\rightarrow$ SCE	.038	3.157	.002	Supported
H4a	AIIF $\rightarrow$ RCF $\rightarrow$ SCE	.045	3.380	.001	Supported
H4b	AIMC $\rightarrow$ RCF $\rightarrow$ SCE	.045	3.291	.001	Supported
H4c	AIPEC $\rightarrow$ RCF $\rightarrow$ SCE	.055	4.121	< .001	Supported

The total indirect effects were .143 for AIIF, .145 for AIMC, and .134 for AIPEC. These totals were closely grouped and were not formally contrasted. Supplementary prediction assessment also showed positive Q^2_{predict} values for all endogenous indicators and an overall predictive advantage over a linear benchmark, although the SCE-specific CVPAT comparison against the linear model was not significant. The evidence therefore supports explanatory relevance and medium, rather than uniformly superior, predictive performance.

5. Discussion and Implications

5.1. Parallel Dynamic Capabilities as Value-Conversion Mechanisms

The results shift attention from resource possession to the organizational work required before AI can contribute to Supply-Chain Efficiency. Sensing, seizing, and reconfiguring were each positively associated with SCE, with coefficients of .255, .227, and .247, respectively. The estimates were relatively close and were not formally contrasted. Substantively, the three mechanisms perform different conversion tasks: sensing turns dispersed signals into timely organizational awareness, seizing turns recognized issues into committed responses, and reconfiguring turns selected responses into durable changes in routines, systems, and operating arrangements. Their

simultaneous significance therefore supports a parallel-mechanism view of AI value realization rather than reliance on a single adaptive capability.

The indirect-effect results reinforce this interpretation. All nine resource–capability–efficiency pathways were supported, and the total indirect effects for AIIF (.143), AIMC (.145), and AIPEC (.134) were closely grouped. AI-enabled operational value is therefore better understood as distributed conversion across several capability channels than as the outcome of one dominant resource or one preferred mechanism. This perspective extends the RBV–DCT link from the question of what AI-related resources a firm possesses to the question of whether the organization can repeatedly convert those resources into awareness, commitment, and operational renewal.

5.2. Theoretical Contributions

Three contributions follow. First, the study integrates RBV and DCT by separating upstream AI resource foundations from the organizational mechanisms that convert those resources into an operational outcome. This moves the explanation from resource possession toward resource-to-performance conversion. Second, the study retains sensing, seizing, and reconfiguring as distinct parallel mechanisms rather than collapsing them into a single dynamic-capability score. Each mechanism contributes independently to SCE, allowing the conversion process to remain theoretically visible. Third, the support for all nine specific indirect effects, together with the closely grouped total indirect effects across AIIF, AIMC, and AIPEC, supports a distributed and complementary account of AI value realization rather than a technology-deterministic or single-channel explanation.

5.3. Managerial Implications

For managers, the main implication is to diagnose the capability bottleneck before purchasing additional AI. A sensing problem calls for integrated data sources, leading indicators, clear alert ownership, and cross-functional interpretation routines. A seizing problem calls for decision rights, response thresholds, budgets, and implementation playbooks that convert analytical insight into timely commitment. A reconfiguring problem calls for hybrid expertise, process redesign, change management, documentation, and cross-training so that successful AI-enabled practices become repeatable organizational routines. This diagnosis-led approach is particularly relevant to SMEs because scarce resources make broad, undirected technology accumulation inefficient (As shown in Table 3).

Table 3. Capability-Bottleneck Diagnosis for Manufacturing SME Managers

Capability bottleneck	Typical symptom	Priority managerial response
Sensing	Late recognition or weak interpretation of supply-chain changes	Integrate data; define leading indicators; assign alert ownership; establish cross-functional reviews
Seizing	Insights are identified but decisions or implementation stall	Clarify decision rights; predefine thresholds; allocate budgets; create response playbooks
Reconfiguring	AI pilots work, but new practices are not embedded or scaled	Develop hybrid expertise; redesign processes; document routines; cross-train staff; govern change

5.4. Limitations

The conclusions should remain bounded by the research design. The data are cross-sectional and self-reported, so the results support associations and indirect pathways rather than causal effects over time. Purposive sampling and the Zhejiang manufacturing context limit external generalization. The model did not estimate AI-resource-to-SCE direct paths, so the indirect effects cannot be labeled full or partial mediation. Finally, the descriptive ranking of the indirect routes was not tested through formal coefficient

contrasts. Longitudinal studies, objective operational measures, multi-region samples, and formal path-difference or configuration analyses would strengthen future evidence.

6. Conclusion

This study explains how AI resource foundations are translated into Supply-Chain Efficiency through three parallel dynamic capability mechanisms. Sensing, seizing, and reconfiguring were each positively associated with SCE and jointly explained 31.2% of its variance. All nine specific indirect effects were statistically significant, and the total indirect effects across AIIF, AIMC, and AIPEC were similar in magnitude. These findings support a distributed conversion view: AI resources become operationally valuable when firms can interpret change, commit to action, and embed revised operating configurations through multiple complementary capability channels. For manufacturing SMEs, the practical implication is to diagnose where the resource-to-performance conversion process is constrained rather than assume that additional AI investment will automatically improve efficiency.

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