FBIM, (2025)

Frontiers in Business Innovations and Management (Open Access)

Volume 02, Issue 12, December 2025,
Publish Date: 09-12-2025
Page No.01-10

Algorithmic Dynamic Capabilities: Orchestrating Ecosystem Strategy and Competitive Advantage in the Age of Artificial Intelligence

Dr. Li Wei
Department of Strategy and Innovation, Tsinghua University Beijing, China

Dr. Elena Sokolova
Graduate School of Business, Higher School of Economics Moscow, Russia

Dr. Nguyen Van Minh
School of Business, Vietnam National University Hanoi, Vietnam

Dr. Kwame Mensah
Department of Organization and Human Resource Management, University of Ghana

ABSTRACT

Purpose: As artificial intelligence (AI) fundamentally reshapes the competitive landscape, traditional strategic frameworks—specifically the Resource-Based View (RBV) and standard Dynamic Capabilities—require recalibration. This paper investigates the emergence of "Algorithmic Dynamic Capabilities," defined as the firm's capacity to utilize machine learning algorithms to autonomously sense environmental changes, seize market opportunities, and reconfigure resources.
Design/Methodology/Approach: Through an integrative theoretical review of strategic management literature (spanning 1984–2021), this study synthesizes concepts from ecosystem strategy, dynamic managerial capabilities, and AI governance. We analyze the intersection of human managerial cognition and algorithmic processing to propose a new microfoundational framework.
Findings: The analysis suggests that sustainable competitive advantage in the digital age is no longer solely dependent on possessing rare, valuable resources (VRIN), but on the architecture of the firm's data ecosystems. We identify a shift from "deliberate strategy" to "emergent algorithmic strategy," where AI enables real-time adaptation that exceeds human cognitive limits. However, we also find that the "Automation-Augmentation Paradox" necessitates a continued, elevated role for human strategic oversight in handling ambiguity and ethical governance.
Originality/Value: This research contributes to the strategic management field by extending the Dynamic Capabilities framework into the domain of AI. It provides a novel typology for understanding how firms can orchestrate complex ecosystems without centralized hierarchical control, offering a roadmap for leaders navigating the post-pandemic digital economy.

KEYWORDS: Dynamic Capabilities, Artificial Intelligence, Business Ecosystems, Strategic Management, Competitive Advantage, Digital Transformation, Algorithmic Strategy.

INTRODUCTION

The landscape of strategic management has undergone a seismic shift in the wake of the global pandemic and the accelerated maturation of digital technologies. For decades, the dominant logic of strategy was predicated on the acquisition of tangible assets and the protection of market position. However, the post-pandemic world, characterized by extreme volatility and interconnectedness, challenges these foundational assumptions. As noted by Hitt, Arregle, and Holmes Jr (2021), the strategic environment has become increasingly complex, requiring firms to navigate not only competitive pressures but also grand societal challenges and rapid technological discontinuities. Central to this transformation is the ubiquitous rise of Artificial Intelligence (AI). No longer merely an operational tool for cost reduction, AI has ascended to the level of strategic architect, fundamentally altering how firms create, capture, and deliver value.

The traditional Resource-Based View (RBV) of the firm, which posits that sustained competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable, remains a cornerstone of management theory (Barney, 1991; Wernerfelt, 1984). Yet, in an era where algorithms and networks "run the world" (Iansiti & Lakhani, 2020), the definition of a "resource" is fluid. Data, unlike physical assets, creates value through aggregation and analysis rather than mere possession. Furthermore, the static nature of early RBV formulations struggles to account for the velocity of modern digital ecosystems. This limitation led to the rise of the Dynamic Capabilities framework, which emphasizes the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece, 2007; Eisenhardt & Martin, 2000).

However, a critical theoretical gap persists. While the literature on Dynamic Capabilities explicitly details the human microfoundations of sensing, seizing, and transforming (Helfat & Martin, 2015), it has not sufficiently accounted for the role of non-human agents in these processes. We are witnessing the emergence of the "Automation-Augmentation Paradox" (Raisch & Krakowski, 2021), where management must decide not just *what* strategy to pursue, but *who*—human or machine—generates it. When an algorithm detects a shift in consumer sentiment and automatically adjusts pricing or supply chain logistics, is this not a "dynamic capability"? If so, how does it differ from the managerial capabilities described by Teece?

This paper seeks to bridge this gap by introducing the concept of "Algorithmic Dynamic Capabilities." We argue that in the age of AI, the ability to orchestrate complex business ecosystems (Adner, 2017) relies on a hybrid architecture of human judgment and algorithmic speed. We posit that AI does not merely support strategy; it enables a new form of "emergent strategy" (Mintzberg & Waters, 1985) that operates at a scale and speed previously unattainable. By synthesizing the literature on dynamic capabilities, business ecosystems, and AI governance, we aim to provide a comprehensive framework for understanding how firms can sustain competitive advantage when the "visible hand" of management is increasingly supplemented by the "digital hand" of the algorithm.

THEORETICAL BACKGROUND

To construct a robust framework for Algorithmic Dynamic Capabilities, we must first revisit the theoretical lineages from which this concept emerges: the Resource-Based View, the Dynamic Capabilities framework, and the nascent literature on AI in management.

The Evolution of the Resource-Based View (RBV)

The origins of modern strategic thought are deeply rooted in the Resource-Based View. Wernerfelt (1984) shifted the focus of strategy from the external market positioning advocated by Porter (1996) to the internal characteristics of the firm. He argued that firms are bundles of resources and that strategy is the art of managing these bundles to maximize returns. Barney (1991) formalized this into the VRIN framework, suggesting that for a resource to confer a sustained competitive advantage, it must be Valuable, Rare, Imperfectly Imitable, and Non-substitutable.

In the context of the 20th-century industrial economy, these resources were often physical: access to raw materials, proprietary manufacturing processes, or prime real estate. However, as the economy shifted toward knowledge and services, the definition of resources expanded to include organizational routines and intellectual property. Today, data is often cited as the "new oil," but this analogy is imperfect. Unlike oil, data is non-rivalrous; its use by one algorithm does not diminish its availability to another. Furthermore, data arguably only becomes a "strategic resource" when processed by sophisticated AI models. Therefore, the possession of data alone (a static resource) is insufficient. It is the *capability* to process that data that matters, pointing us toward dynamic capabilities.

Dynamic Capabilities in a High-Velocity World

Teece (2007) explicated the microfoundations of dynamic capabilities to explain why some firms succeed in rapid innovation while others fail despite having ample resources. He categorized these capabilities into three clusters:

1. **Sensing:** Identification and assessment of opportunities and needs.
2. **Seizing:** Mobilization of resources to address needs and capture value.
3. **Transforming:** Continued renewal of the organization to maintain relevance.

Eisenhardt and Martin (2000) further argued that in high-velocity markets, dynamic capabilities are not vague, abstract abilities but specific, identifiable processes—such as product development routines or strategic decision-making protocols. Helfat and Martin (2015) emphasized the critical role of *Dynamic Managerial Capabilities*, highlighting that managerial cognition, social capital, and human capital are the primary drivers of strategic change. This human-centric view implies that "sensing" is a function of a manager reading a market report, and "seizing" is a board of directors approving an investment.

The limitation of this view in the 2020s is evident. The volume of data generated by global ecosystems exceeds human cognitive processing limits. Grand challenges (George et al., 2016) and global market shifts occur with such complexity that human intuition is often insufficient or prone to bias. This necessitates the integration of AI into the very fabric of dynamic capabilities.

Ecosystems and the AI Shift

The unit of analysis in strategy has moved beyond the single firm to the ecosystem. Adner (2017) defines an ecosystem as a structure of multilateral interdependence. In an ecosystem, value is created not just by the focal firm but by the orchestrated efforts of complementors, suppliers, and customers. Petricevic and Teece (2019) note that globalization and structural reshaping require firms to manage these interdependencies across borders.

Iansiti and Lakhani (2020) argue that AI enables a new operating model for these ecosystems. By automating operational decisions and personalizing customer experiences at scale, AI removes the traditional constraints of scope and scale. A digital firm can serve millions of customers with the same personalized attention as a dozen, provided the algorithms are robust. This "digital scale" forces a rethinking of Porter's (1996) trade-offs. It is no longer necessarily true that a firm must choose between cost leadership and differentiation; AI allows for both simultaneously by optimizing backend costs while tailoring frontend experiences.

METHODOLOGY: A CONCEPTUAL TYPOLOGY

Given the nascent stage of "Algorithmic Dynamic Capabilities" as a formal construct, this paper adopts an integrative theoretical approach. We do not present empirical data from a specific sample, as the phenomenon is currently outpacing standard longitudinal data collection methods. Instead, we employ a conceptual typology analysis, synthesizing divergent streams of literature to propose a new theoretical framework.

We utilized the references provided, which represent seminal works in strategic management, to ground our definitions. The analysis proceeds by deconstructing the three pillars of Teece's (2007) framework—Sensing, Seizing, and Transforming—and reconstructing them through the lens of AI and ecosystem theory.

Construct Definitions:

- **Algorithmic Sensing:** The capacity of a firm to utilize machine learning and predictive analytics to scan internal and external environments for patterns, anomalies, and opportunities without direct human intervention in the initial data filtering phase.
- **Automated Seizing:** The ability of organizational systems to execute resource allocation decisions, pricing adjustments, and contract deployments (e.g., via smart contracts) in real-time response to sensed stimuli.
- **Hybrid Transforming:** The organizational capability to restructure the firm's boundaries, culture, and business model through a collaborative process between human strategic leadership and algorithmic insights.

Analysis & Propositions: The Microfoundations of Algorithmic Capabilities

To truly understand how AI reshapes competitive advantage, we must move beyond the macro-level observation that "AI is important" and dissect the micro-processes of strategy. The following sections expand on the traditional dynamic capabilities framework, proposing specific mechanisms by which AI alters the sensing, seizing, and transforming logic.

From Managerial Sensing to Algorithmic Omniscience

In the traditional conception of dynamic capabilities, "sensing" involves activities such as R&D, market research, and probing customer needs. This is historically a labor-intensive, time-lagged process. A firm might commission a market study and receive results three months later, by which time consumer preferences may have shifted.

Proposition 1: Algorithmic Sensing allows for the transition from episodic environmental scanning to continuous, real-time reality mining.

Algorithmic sensing differs from human sensing in three critical dimensions: coverage, granularity, and predictive horizon.

- **Coverage:** While a human manager can monitor a finite number of competitors or variables, AI systems can ingest unstructured data from social media, satellite imagery, IoT sensors, and financial reports globally. This creates a "panoptic" view of the ecosystem (Iansiti & Lakhani, 2020).
- **Granularity:** Traditional sensing aggregates data (e.g., "sales in the Northeast region"). Algorithmic sensing operates at the level of the individual transaction or user behavior, allowing for "markets of one."
- **Predictive Horizon:** Through deep learning and neural networks, algorithmic sensing moves from descriptive analytics (what happened) to predictive (what will happen) and prescriptive (what we should do).

However, this creates a new challenge: the signal-to-noise ratio. As Foss and Saebi (2017) noted in the context of business model innovation, the key is not just identifying changes but interpreting them correctly. If an algorithm detects a spike in demand, is it a temporary anomaly or a structural shift? Here, the "Automation-Augmentation Paradox" (Raisch & Krakowski, 2021) becomes salient. The algorithm provides the signal, but the *meaning* of that signal often requires human contextualization. Therefore, we propose that the most successful firms are not those that automate sensing entirely, but those that build interfaces where algorithmic outputs trigger human strategic conversations.

From Bureaucratic Seizing to Automated Orchestration

Once an opportunity is sensed, the firm must "seize" it by mobilizing resources. In large multinational enterprises, this is notoriously difficult due to structural inertia. Allocating capital requires committee approvals, bureaucratic workflows, and political negotiation.

Proposition 2: Automated Seizing enables the decoupling of resource allocation from bureaucratic hierarchy, allowing for high-frequency strategic adjustments.

This is most visible in digital advertising markets and high-frequency trading, but it is spreading to physical supply chains. Consider a global logistics firm utilizing AI. If "Algorithmic Sensing" predicts a weather disruption in the South China Sea, "Automated Seizing" does not wait for a VP of Logistics to hold a meeting. The system automatically reroutes containers, updates pricing models for expedited shipping, and notifies suppliers of delay—all within milliseconds.

This represents a fundamental shift in the "nature of the firm" as described by Coase. The transaction costs of internal coordination are drastically reduced. However, this automation of seizing implies a surrender of control. Teece (2018) emphasizes that business models are the architecture of value creation. If algorithms are dynamically altering pricing and resource flows, they are effectively modifying the business model in real-time. This requires a robust set of "guardrails" or "governance algorithms" to ensure that the automated decisions align with the firm's long-term strategic intent and ethical standards.

Deep Dive: The Microfoundations of Hybrid Transforming

(This section represents the expanded core analysis, elaborating heavily on the third pillar of dynamic capabilities.)

The third pillar of dynamic capabilities, **Transforming** (or Reconfiguring), is perhaps the most complex and least understood in the context of AI. While sensing and seizing can often be reduced to informational processing tasks—data in, decision out—transforming involves the fundamental restructuring of the organization's assets, structure, and culture. It is the process of "creative destruction" applied internally. In the analog era, transformation was an episodic, painful intervention: a corporate restructuring, a merger, or a divestiture, usually driven by a crisis.

In the age of AI, we argue for **Hybrid Transforming**, a continuous, evolutionary process where the organization morphs fluidly based on data feedback loops. This section breaks down the microfoundations of this capability into three distinct components: **Asset Orchestration**, **Cognitive Re-alignment**, and **Ecosystem Governance**.

Algorithmic Asset Orchestration

Traditional asset orchestration (Helfat & Martin, 2015) relies on managerial fiat to move talent, capital, and technology between divisions. This is often hindered by information asymmetry; a CEO rarely knows exactly which division has excess capacity or which talent is underutilized. AI systems solve this information asymmetry, enabling what we term "Liquid Asset Allocation." For instance, in a professional services firm, an AI system can analyze the skill sets, current workload, and past performance of thousands of employees to assemble project teams dynamically. This is not merely a database query; it is an optimization problem that balances client needs, employee development goals, and profitability.

Furthermore, this extends to physical assets. In the manufacturing sector (Industry 4.0), "digital twins" allow firms to simulate production line reconfigurations virtually before physical implementation. The "transforming" capability thus moves from a physical trial-and-error process to a simulated optimization process. The algorithm simulates a thousand potential reconfigurations of the factory floor to optimize for a new product line, and the human manager selects the optimal scenario. This drastic reduction in the cost of experimentation allows firms to transform their operations more frequently and with lower risk (Teece, 2007).

Cognitive Re-alignment and the Absorptive Capacity of AI

Transformation is not just about moving boxes; it is about changing minds. One of the greatest barriers to strategic change is cognitive inertia—managers sticking to old mental models (Mintzberg & Waters, 1985).

AI acts as a counterweight to cognitive bias. By presenting data that contradicts intuition, AI forces a "Cognitive Re-alignment." However, this is where the *human* element of Hybrid Transforming is paramount. An algorithm can suggest that a core product line is dying, but it cannot empathize with the workforce that produces it. The "Transforming" capability, therefore, requires leaders who are skilled in *change management*. They must translate the "cold" logic of the algorithm into a "warm" narrative that motivates the organization.

Moreover, the firm must develop what Cohen and Levinthal termed "absorptive capacity"—the ability to recognize the value of new information, assimilate it, and apply it. In an AI context, this means the firm must have the technical and cultural capacity to absorb algorithmic insights. If the algorithm suggests a radical pivot, but the organizational culture is risk-averse and hierarchical, the transformation will fail. Thus, a key microfoundation of Hybrid Transforming is the cultivation of an "algorithmic culture"—one that values data over rank and experimentation over status quo.

Ecosystem Governance and Structural Reshaping

Finally, Transforming in the modern era extends beyond the firm's boundaries. As Petricevic and Teece (2019) argue, globalization and innovation require managing complex interdependencies. Firms are no longer islands; they are nodes in a network.

AI facilitates "Ecosystem Governance." Consider a platform company like Uber or Airbnb. They do not own the cars or the houses; they own the *algorithm* that governs the interaction between providers and users. The "transformation" of these firms often involves tweaking the algorithm to incentivize different behaviors (e.g., surge pricing to encourage drivers to work during rain).

This leads to a profound insight: In digital ecosystems, **Strategy is Code**. The strategic intent of the firm is encoded in the algorithms that govern the ecosystem. To "transform" the strategy is to rewrite the code. This requires a new breed of strategic leader who understands both the business logic and the technological architecture. The separation between "IT strategy" and "Business strategy" has dissolved.

The Paradox of Control in Hybrid Transformation

A critical tension arises here. As firms delegate more transforming capabilities to algorithms (e.g., automated supply chain reconfiguration), they risk creating "black box" organizations where the logic of operation is opaque even to the owners. This touches on the "Automation-Augmentation Paradox" (Raisch & Krakowski, 2021). If the system optimizes for short-term profit at the expense of long-term reputation or sustainability, the firm may transform itself into a pariah.

Therefore, Hybrid Transforming requires a "Human-in-the-loop" governance structure. We propose a tiered approach:

- **Tier 1 (Operational):** Algorithms autonomously reconfigure routine workflows and resource allocations.
- **Tier 2 (Tactical):** Algorithms propose structural changes (e.g., entering a new market segment based on data), but human managers validate the decision.
- **Tier 3 (Strategic/Normative):** Humans define the high-level goals and ethical constraints (the objective function) that the algorithms strive to optimize.

This tiered approach ensures that the firm maintains the agility of AI while retaining the strategic intent and moral compass of human leadership. It resolves the paradox by assigning distinct roles: the AI provides the *efficiency* of transformation, while the human provides the *purpose* of transformation.

DISCUSSION

Theoretical Implications: Revisiting "What is Strategy?"

Porter (1996) famously argued that "operational effectiveness is not strategy." Strategy, he claimed, is about choosing a unique position and making trade-offs. In the age of AI, this distinction blurs. If operational effectiveness (driven by AI) becomes so advanced that it allows for hyper-personalization and rapid adaptation, it creates a barrier to entry that is indistinguishable from a strategic position.

Our framework suggests that "Algorithmic Dynamic Capabilities" are the modern equivalent of Porter's "activity systems." A competitor might copy a firm's pricing or product features, but they cannot easily replicate the complex, data-rich ecosystem of algorithms that powers the sensing, seizing, and transforming processes. This supports the RBV argument that history and path dependence matter (Barney, 1991). The AI model that has been trained on ten years of proprietary data is a resource that is valuable, rare, inimitable, and non-substitutable.

Managerial Implications: The Orchestrator Leader

For practitioners, the shift to algorithmic strategy requires a re-evaluation of leadership skills. The successful CEO of the 2030s will not be the "decider-in-chief" but the "architect-in-chief." Their role is to design the system—the combination of human teams and AI agents—that generates decisions.

This aligns with Mintzberg and Waters' (1985) concept of emergent strategy. The leader sets the broad "deliberate strategy" (the vision, the ethical guardrails, the target markets), but allows the "emergent strategy" to bubble up from the algorithmic interactions with the market. Leaders must become comfortable with ambiguity and loss of granular control, trusting the "digital hand" to manage the details while they manage the ecosystem.

Societal and Grand Challenges

Finally, we must address the role of AI in tackling grand challenges (George et al., 2016). Climate change, pandemics, and social inequality are systemic problems that require systemic solutions. Algorithmic dynamic capabilities enable firms to model complex systems and optimize for variables beyond profit—such as carbon footprint reduction or supply chain ethics.

For example, an AI-driven supply chain can dynamically optimize routes not just for speed, but for fuel efficiency, seizing the opportunity to be a sustainability leader. This suggests that the "Transforming" capability can be directed toward social good, aligning the firm's purpose with societal needs.

Limitations and Future Research

This paper is conceptual and limited by the lack of longitudinal empirical data on mature AI-driven firms. Future research should focus on empirical validation of the proposed "Algorithmic Dynamic Capabilities" construct. Specifically, scholars should investigate the failure modes: What happens when algorithmic sensing generates false positives? How do firms recover from automated seizing errors? Additionally, the ethical implications of algorithmic management on the workforce require urgent attention.

CONCLUSION

The integration of Artificial Intelligence into strategic management represents more than a technological upgrade; it is a paradigm shift in how firms navigate the world. By revisiting the foundational theories of the Resource-Based View and Dynamic Capabilities, we have proposed that the firm of the future is a hybrid entity. It leverages "Algorithmic Dynamic Capabilities" to sense the environment with omniscience, seize opportunities with automation, and transform its structure with fluid precision.

However, the "Automation-Augmentation Paradox" reminds us that the machine is only as good as the purpose defined for it. As we move forward, the essence of strategy remains distinctly human: to define value, to set the moral compass, and to ask the questions that the algorithms cannot yet conceive. The competitive advantage of tomorrow belongs to those who can harmonize the speed of silicon with the wisdom of the human spirit.

REFERENCES

1. Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. Journal of Management, 43(1), 39–58.
2. Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.
3. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, 21(10-11), 1105–1121.
4. Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation: How far have we come, and where should we go? Journal of Management, 43(1), 200–227.
5. George, G., Howard-Grenville, J., Joshi, A., & Tihanyi, L. (2016). Understanding and tackling grand challenges: A research agenda for management scholarship. Academy of Management Journal, 59(6), 1880–1895.
6. Helfat, C. E., & Martin, J. A. (2015). Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. Journal of Management, 41(5), 1281–1312.
7. Hitt, M. A., Arregle, J. L., & Holmes Jr, R. M. (2021). Strategic management theory in a post-pandemic world. Journal of Management Studies, 58(1), 259–264.
8. Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI: Strategy and leadership when algorithms and networks run the world. Harvard Business Review Press.
9. Mintzberg, H., & Waters, J. A. (1985). Of strategies, deliberate and emergent. Strategic Management Journal, 6(3), 257–272.
10. Petricevic, O., & Teece, D. J. (2019). The structural reshaping of globalization: Implications for strategic sectors, profiting from innovation, and the multinational enterprise. Journal of International Business Studies, 50(9), 1487–1512.
11. Porter, M. E. (1996). What is strategy? Harvard Business Review, 74(6), 61–78.
12. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210.
13. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350.
14. Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49.
15. Wernerfelt, B. (1984). A resource-based view of the firm. Strategic Management Journal, 5(2), 171–180.