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INFUSING ARTIFICIAL INTELLIGENCE INTO STRATEGY: SYNTHESIZING FIVE CLASSIC DEBATES

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ABSTRACT

This paper explores how artificial intelligence (AI) transforms the foundations of strategic management theory. While traditional debates have centered on industry structure and resource-based perspectives, AI introduces a theoretical discontinuity that challenges assumptions about cognition, resources, and firm boundaries. We examine five influential streams: Behavioral Strategy, Microfoundations, Ecosystems and Platforms, Stakeholder Resource-Based View, and Strategy-as-Practice, to assess how AI reshapes their core premises. Our analysis reveals that AI creates hybrid cognitive architectures, embeds algorithmic actors into microfoundations, reconfigures ecosystems around foundation models, redistributes resource control to stakeholders, and alters strategizing practices through continuous, AI-augmented processes. The paper concludes with an agenda for empirical research, emphasizing multi-level analysis, algorithmic governance, and ethical considerations in an AI-infused strategic landscape.

Keywords *artificial intelligence, strategic management theory, behavioral strategy, microfoundations, digital ecosystems, human-AI collaboration, algorithmic governance.*

1. Introduction

Strategic management has always been centrally concerned with explaining persistent differences in firm performance. From the earliest works in the field, scholars have attempted to answer a deceptively simple question: Why do some firms succeed while others fail?

Two dominant perspectives, the external industry configuration view and the resource-centric perspective (resource-based view, RBV), have provided the field's foundational answers. The external industry configuration

perspective, anchored in industrial organization economics (Porter 1980), emphasizes how competitive positioning within an industry and the structure of the external environment drive sustainable rents. By contrast, the RBV (Wernerfelt 1984; Barney 1991) argues that firm-level heterogeneity rooted in valuable, rare, inimitable, and non-substitutable resources is the essential source of strategic edge.

Competitive advantage (Porter 1980; Barney 1991; Wernerfelt 1984) and bounded rationality frameworks (Simon 1947; Cyert and March 1963; Nelson and Winter 1982) provided the initial scaffolding for this research, while subsequent developments of the knowledge-based view (Grant 1996; Nonaka 1994) and stakeholder theory (Freeman 1984) expanded the field's perspective on value creation. Over the last three decades, scholars have devoted considerable energy to synthesizing these perspectives, whether by integrating industry-level and firm-specific mechanisms, proposing multilevel theories of capabilities, or reconciling structure and agency in the genesis of advantage. This interpretation is extended by incorporating contemporary artificial intelligence (AI)-driven dynamics, offering a novel synthesis beyond classical frameworks.

Yet the contemporary emergence of AI, as both a technological paradigm and an organizational force, poses challenges that extend far beyond traditional attempts at synthesis. AI undermines long-standing assumptions about managerial rationality, the nature of organizational resources, and even the unit of analysis in strategy theory. Machine learning systems redefine what constitutes human and nonhuman agency. Generative AI systems alter the positioning, domain-specific variances, transparency and cost structure of information processing, representation, and recombination (Bhuyan et al. 2025; Tripathi et al. 2025; Chidipothu et al. 2025). Foundation models (FMs) transcend firm boundaries, embedding themselves into ecosystems, supply chains, and institutional infrastructures. They also reshape the dynamics between firms and their stakeholders, altering power, participation, and co-creation. In short, AI constitutes a discontinuity with implications not only for strategy practice but for strategy theory itself.

Despite rapid practitioner interest in AI's strategic implications, academic strategy research has only begun to confront the theoretical consequences. Emerging work in strategy research highlights the role of AI in reshaping competition (Cockburn et al. 2018), augmenting managerial cognition (Shrestha et al. 2019), transforming organizational capabilities (Raisch and Krakowski 2021), restructuring ecosystems (Hannah and Eisenhardt 2018), and accelerating learning processes (Wu and Wang 2021). These contributions provide important starting points, yet the field lacks a systematic account of how AI reverberates across strategy's key theoretical directions and what a synthetic, AI-informed strategy theory might entail.

This paper seeks to fill that gap by examining five influential theoretical trends in contemporary strategy research and evaluating how AI reshapes each:

1. *Behavioral Strategy*: How does AI alter assumptions about cognition, limited rationality, emotions, heuristics, and social influence in strategic decision-making?
2. *Microfoundations*: How does AI challenge existing models of individual-level heterogeneity, interaction patterns, and the human foundations of firm-level outcomes?
3. *Ecosystems and Platforms*: How does AI reconfigure interconnected network architectures, multiactor complementarities, and the governance of distributed innovation?
4. *Stakeholder RBV*: How does AI transform resource co-creation with stakeholders, introduce new forms of value appropriation, and shift power across stakeholder groups?
5. *Strategy-as-Practice (SAP)*: How does AI reshape strategizing as lived practice, i.e., the tools, routines, interactions, and situated actions through which strategy is performed?

These five areas are not exhaustive; many additional streams, dynamic capabilities, evolutionary economics, real options, and knowledge-based theories, are likewise affected by AI. However, these five represent major contemporary directions in mainstream strategy research, and together they offer a multifaceted foundation for exploring how AI destabilizes core theoretical assumptions.

1.1. AI as a Transformational Theoretical Shock

Much like the rise of digital platforms in the early 2000s, AI functions as what theorists might call a general-purpose technology, but one whose generality and adaptivity are unprecedented. Machine learning algorithms are not simply tools; they are evolving systems capable of learning patterns, generating outputs, and increasingly acting with a degree of autonomy (Jordan and Mitchell 2015). This "agentic" dimension of AI, its capacity to make recommendations, initiate actions, and influence decision flows, creates theoretical complexity that extends beyond automation or digitization. From a strategy theory standpoint, AI simultaneously affects:

- the cognition of managers (what they perceive, ignore, and prioritize)
- the resources firms control (data, models, and algorithmic capabilities)
- the structure of competition (winner-take-all dynamics, scalability of adaptive learning systems)
- the nature of ecosystems (interdependence among models, data flows, and platforms)
- stakeholder dynamics (distributional consequences, new power asymmetries)
- strategic practice itself (expansively fluid intelligence, tools, routines, decision processes, and the locus of agency)

Thus, AI forces a reconsideration of strategy's foundational ontology. It forces us to ask fundamental questions: What is a resource? Who or what is a strategist? What is the boundary of a firm? How do capabilities emerge when "actors" include both humans and intelligent systems? What does strategic edge mean when adaptive intelligence, not static resources, becomes the basis of primary value creation?

These ontological questions echo themes in the field's recent interest in behavioral realism, multilevel theorizing, and dynamic, process-oriented views of strategic edge. Yet AI pushes each of these themes into new territory, requiring both conceptual innovation and integrative synthesis.

1.2. Toward an AI-Infused Strategy Theory

Understanding AI-infused strategy requires moving beyond purely technological or economic framings to embrace sociotechnical perspectives. Actor-network theory provides a valuable lens for understanding how algorithmic actors reshape organizational networks (Latour 2005; Callon 1984). The concept of sociomateriality helps us theorize the inseparability of human and algorithmic agencies in strategic practice (Orlikowski 2007; Orlikowski and Scott 2008; Leonardi 2011). These perspectives reveal how AI transforms not just decision outcomes but the very fabric of organizational life. Moreover, institutional theory reminds us that AI adoption reflects not only efficiency calculations but also legitimacy pressures and mimetic isomorphism (DiMaggio and Powell 1983).

AI has been broadly defined as a cluster of "technologies that mimic the functions and expressions of human intelligence, specifically cognition, logic, learning, adaptivity and creativity" (Samuel 2021; Samuel et al. 2022, 2024). While this ontologically grounded definition captures AI's essential characteristics from a contemporary perspective, it remains insufficient for advancing strategy research and practice. Strategic management requires not merely an understanding of what AI *is*, but rather a conceptualization of what AI *does*—how it transforms the mechanisms through which firms create and capture value (Dwivedi et al. 2021). Following our analysis of AI's influence on five major strategy theories, we present a contextualized articulation of AI that emphasizes its functional impacts on competitive dynamics, organizational capabilities, and the fundamental processes of strategizing itself.

One of this paper's central arguments is that AI is not simply an empirical phenomenon requiring new studies, but a transformative systemic shock that necessitates a re-evaluation of long-standing strategy theories (Galaz et al. 2021). However, rather than discarding the field's existing insights, AI may provide an integrative glue that helps synthesize the external industry configuration and resource-based traditions. AI can also act as a disruptor and replacer, which affects both external and internal sources of advantage (Wan and Zhao 2024). It alters industry-level dynamics (data network effects, digital hub competition) while also reshaping firm-specific resources and capabilities (proprietary data, model fine-tuning routines, organizational learning loops).

Therefore, AI may enable a new synthesis in strategy theory, one that reconciles external and internal explanations by focusing on learning processes, cross-boundary data flows, and multiactor complementarities as fundamental drivers of advantage. The five theoretical trends examined in this paper each illuminate a different facet of this synthesis:

1. Behavioral strategy reveals how AI changes the psychology and cognition of strategizing.
2. Microfoundations explain how AI alters the building blocks of capabilities and interactions.
3. Ecosystem theories show how AI restructures the locus of competition.
4. Stakeholder RBV highlights distributed value creation and ethical-political consequences.
5. SAP exposes how AI transforms strategizing as an enacted, material practice.

By analyzing how AI transforms these areas and synthesizing them into a comprehensive framework, this paper aims to articulate a forward-looking theory of agentic AI and strategic management.

1.3. Structure of the Paper

The remainder of the paper is organized as follows. [Section 2](#) reviews five major theoretical trends influential in contemporary strategy research. [Section 3](#) outlines how AI intersects with and challenges existing models in each area, drawing extensively on recent SMJ contributions. [Section 4](#) presents a comparative table contrasting pre-AI and post-AI perspectives on the determinants of strategic edge across the five theoretical domains. [Section 5](#) concludes with implications for theory, methods, and practice.

This paper conceptualizes AI not as a technological add-on but as a transformative force that necessitates a fundamental shift in the assumptions underpinning strategy theory. As AI becomes increasingly embedded in organizations, ecosystems, and sociotechnical infrastructures, strategic management research must develop a theoretical vocabulary that addresses this new reality. The goal of this paper is to take a step toward such a vocabulary.

2. Five Influential Trends in Strategy Research

The emergence of FMs represents a fundamental shift in AI capabilities, with profound implications for organizational strategy ([Bommasani et al. 2021](#); [Xu et al. 2025](#)). These models demonstrate general-purpose learning abilities that challenge traditional assumptions about technological specialization and competitive advantage. Recent research suggests AI may fundamentally reshape economic growth trajectories ([Aghion et al. 2019](#)), labor markets ([Bessen et al. 2025](#)), and the nature of human-machine collaboration ([Passerini et al. 2025](#)). The competitive dynamics among FM providers introduce new questions about market structure and governance ([Haim and Meyer 2024](#)), while the algorithmic mediation of organizational relationships creates novel power structures ([Gutiérrez 2024](#)). These developments demand new forms of digital leadership attuned to AI-specific capabilities ([Hossain et al. 2025](#)).

Over the last three decades, strategic management has evolved from a field primarily concerned with competitive positioning and firm-level resources to one that increasingly incorporates insights from behavioral science, organizational microdynamics, stakeholder engagement, practice-based perspectives ([Guerras-Martin et al. 2014](#)), and ecosystems theory ([Jacobides et al. 2018](#)). These developments expand the theoretical boundary of strategy while also sharpening analytical tools for understanding how organizations create and appropriate value. In this section, we review five major theoretical trends that have become central to strategy research and that form the backbone of our analysis of how AI transforms theoretical assumptions.

The five areas, behavioral strategy, microfoundations, ecosystems, stakeholder RBV, and SAP, were selected because they have shaped significant streams of inquiry in the field and because they capture different layers of analysis: cognition and behavior, individual-level interactions, multiactor systems, stakeholder relationships, and the situated practices of strategists. Together, these streams illuminate the diverse mechanisms through which strategic edge develops and evolves.

2.1. Behavioral Strategy and the Psychology of Strategizing

The behavioral turn in strategic management emerged as a response to critiques of the rational-actor model inherited from classical economics. Early behavioral insights from [Simon \(1947\)](#), [Cyert and March \(1963\)](#), and others emphasized limited rationality, satisficing, routines, and the sociopolitical nature of organizational decision-making. Yet these ideas were not fully integrated into strategy until the 2000s, when scholars like [Gavetti \(2005\)](#), [Levinthal \(2011\)](#), and [Powell et al. \(2011\)](#) mobilized cognitive and psychological insights to explain strategic behavior more realistically.

Behavioral strategy focuses on several core dimensions. The first of these are cognition and mental models. Strategic decision-makers rely on cognitive schemas, analogies, frames, and heuristics to interpret environments. These mental models shape what firms perceive, how they attend to information, and how they make sense of competitive contexts. Research by [Gary and Wood \(2011\)](#), [Eggers and Kaplan \(2013\)](#), and [Kaplan \(2011\)](#) demonstrates how managerial cognition affects strategic choices under ambiguity, complexity, and competitive pressure.

In addition, behavioral strategy focuses on biases and heuristics. Strategic choices are systematically shaped by psychological biases, overconfidence, loss aversion, anchoring, escalation of commitment, and others (Powell et al. 2011). Although biases can create performance traps, heuristics sometimes facilitate effective strategizing by simplifying complexity.

Shifting from a purely economic approach, behavioral strategy also takes emotion and social influence into consideration. Recent extensions acknowledge affect, identity, status, and social dynamics as important determinants of strategic behavior (McDonald and Westphal 2013). Emotions influence risk-taking, conflict resolution, alliance decisions, and entrepreneurial judgment.

The importance of behavioral realism in strategy theory is also foregrounded. The core argument of behavioral strategy is that realistic assumptions about human cognition and emotion improve explanatory power (Gavetti 2012). Instead of assuming perfect rationality, behavioral strategy assumes bounded, structured, and socially embedded rationality.

This perspective has become essential for understanding how decision-makers formulate strategy, interpret competitive signals, and navigate uncertainty, making it a crucial foundation for analyzing how AI alters managerial cognition and strategic judgment.

2.2. Microfoundations of Strategy

While behavioral strategy emphasizes the cognitive and psychological processes of individuals, the microfoundations movement addresses a broader question: How do individual-level actions and interactions generate firm-level outcomes?

The microfoundational agenda emerged around 2010 as scholars grew increasingly dissatisfied with “black box” explanations of capabilities, routines, and performance heterogeneity. Research by Felin and Foss (2005), Felin et al. (2015), and Barney and Felin (2013) emphasized the need for theories that explicitly articulate how individuals, through their attributes, behaviors, and interactions, create and modify organizational-level constructs. This interpretation is extended by incorporating contemporary AI-driven dynamics, offering a novel synthesis beyond classical frameworks.

Three themes define microfoundational work. The first is *individual heterogeneity*. Microfoundation theorists believe that capabilities and routines originate from the skills, motivations, knowledge, and cognitive differences among individuals (Felin and Foss 2005). Even highly abstract constructs such as adaptive capabilities or absorptive capacity must ultimately be grounded in individuals’ abilities to sense, interpret, and act.

The second theme involves *interactions and coordination mechanisms*. Individuals rarely act in isolation; organizational outcomes arise through structured interactions supported by coordination mechanisms, relational contracts, communication patterns, and shared understandings. Microfoundations emphasize how patterns of interaction, such as communication networks or cross-functional teaming, produce emergent outcomes (Ployhart and Moliterno 2011).

Finally, microfoundations address *aggregation and emergence*. A key contribution of microfoundations is to clarify how individual actions accumulate into organizational phenomena. This involves understanding emergence: firm-level capabilities result not from simplistic summation but from complex, interdependent interactions. Organizational routines, for example, emerge from repeated interaction patterns but acquire stability through collective enactment.

The microfoundational lens is valuable for studying AI because AI alters who (or what) performs actions, how individuals interact with systems, and how firm-level outcomes emerge from human-AI hybrids. The shift from purely human microfoundations to sociotechnical microfoundations challenges the boundary conditions of the field.

2.3. Ecosystems, Platforms, and Meta-Organizations

Over the past decade, ecosystems and platforms have become defining concepts in strategy research. Traditional strategy theories conceptualized competition as occurring between firms within industries or markets. Interconnected network thinking expands this by focusing on loosely coupled, multiactor systems in which value creation depends on complementarities among firms, users, regulators, and institutional actors. Ecosystem theory has evolved from early work on innovation ecosystems (Adner 2006; Autio and Thomas 2014) to more nuanced understandings of platform-based value creation (Gawer 2014; Gawer and Cusumano 2014). The modular architecture of digital platforms (Baldwin and Clark 2000) enables new forms of ecosystem orchestration. The emergence of AI

platforms introduces additional complexity in how value is created and captured across eco- system participants (Jacobides et al. 2019).

Three distinctive ideas underpin ecosystems research, The first relates to the *primacy of complementarities*. Firms create value not in isolation but through complementarities, among modules, technologies, and actors. The success of a digital hub depends on the quality and diversity of complementary innovations (Hannah and Eisenhardt 2018; Kapoor and Agarwal 2017).

The second theme involves *distributed and interdependent innovation*. In ecosystems, innovation is distributed across multiple firms and actors. No single firm controls all critical resources (Adner 2017). Meta-organizations, organizational forms where membership is composed of other organizations, shape coordination, governance, and conflict resolution.

The third idea is that of *winner-take-most dynamics and governance* (Schrepel and Pentland 2025). Ecosystems and platforms often exhibit network effects, scale economies, and data-driven learning loops that produce dominant positions for a few firms. This creates new governance challenges, including power asymmetries, access control, and rule-setting authority. Interconnected network theory provides a compelling framework for understanding AI because AI development, deployment, and improvement occur in highly interdependent environments (Shur-Ofry 2024). FMs rely on data ecosystems, model hubs, cloud infrastructures, and communities of developers. Competitive dynamics increasingly unfold not only between firms but between ecosystems of algorithms, data flows, and complementarities (Schrepel and Pentland 2025).

2.4. Stakeholder RBV

Classic RBV focuses on firm-controlled resources as sources of advantage. Stakeholder RBV represents a major shift, arguing that participating entities, not just shareholders, play central roles in resource creation, development, and appropriation (Barney et al. 2021). In a sense, it expands the boundaries where firm-level research can be enacted.

Some of the key premises of stakeholder RBV include:

Stakeholders as Resource Contributors: Stakeholders (employees, suppliers, customers, communities, regulators) contribute tangible and intangible resources: knowledge, legitimacy, relationships, trust, data, and social support. These resources shape a firm's ability to generate and sustain strategic edge (McGahan 2021).

Co-Creation and Co-Specialization: Value emerges through collaborative interactions among firms and stakeholders. Co-specialized assets, resources whose value depends on relational fit, create mutual dependence. The more stakeholders are integrated into capability development, the more they influence strategic outcomes (Harrison et al. 2010).

Stakeholder Power and Value Appropriation: Stakeholders vary in their power, claims, salience, and ability to capture value. Stakeholder RBV highlights distributional questions: who benefits from resource creation, and under what conditions? This perspective suggests that value creation is a fundamentally relational process, whereby the firm's competitive success depends on its ability to effectively manage and integrate the diverse interests of its stakeholder network (Freeman et al. 2021).

Ethical and Sociopolitical Considerations: Many strategic resources are socially constructed, making ethical and political issues such as fairness, equity, and transparency, central to understanding competitive advantage. This is particularly relevant for AI, where issues of data rights, privacy, surveillance, and algorithmic fairness introduce new stakeholder tensions. The potentially severe consequences of AI mismanagement, whether through intentional misuse or unintended harm, necessitate moving beyond discourse on "human-centered AI" toward frameworks that actively enhance human capabilities and wellbeing. Strategic advantage increasingly depends on organizations' ability to deploy AI in ways that demonstrably elevate human agency, augment rather than diminish human capacities, and create value that stakeholders experience as genuinely beneficial rather than extractive (Kashyap et al. 2024; Samuel et al. 2024). Firms that treat ethical considerations as constraints to be minimized risk stakeholder backlash and regulatory intervention, while those that embed human enhancement principles into AI strategy may gain legitimacy-based advantages and more durable stakeholder relationships.

Stakeholder RBV is essential to understanding how AI impacts strategy because AI depends on data derived from stakeholders, shapes stakeholder experiences, and redistributes value and risk across stakeholder groups (Ozdemir et al. 2023; Kashyap et al. 2024). The successful reinforcement of ecological sustainability at the ecosystem level often depends on the diversity of the stakeholder network, as collaborations with secondary stakeholders are specifically associated with the development of eco-innovations (Ozdemir et al. 2023).

2.5. SAP

SAP shifts attention from strategy as a property of firms to strategy as something people do, emphasizing everyday activities, tools, and routines through which strategizing is enacted. Users of SAP (Whittington 2006) argue that traditional perspectives obscure the micro-level practices that produce strategy. Current approaches to SAP focus on emphasizing dynamism in strategic theory and practice (Prashantham and Healey 2022).

SAP focuses on three interrelated dimensions:

Practitioners: It is important to ask who we refer to when we talk about strategists. SAP researchers believe that beyond top managers, strategists include middle managers, consultants, analysts, and increasingly, technological artifacts and systems.

Practices: What tools, methods, and techniques do strategists use? Practices include forecasting tools, decision frameworks, performance dashboards, analytical techniques, and planning routines.

Praxis: What do strategists actually do in day-to-day settings? Praxis includes meetings, presentations, planning cycles, negotiations, sensemaking, and interactions.

A distinguishing feature of SAP is its materiality: strategizing is mediated by artifacts, spreadsheets, slide decks, dashboards, analytics tools. This makes SAP particularly relevant for understanding how AI transforms strategizing because AI creates new tools, embeds itself in existing practices, and acts as a quasi-strategist by participating in decision processes.

2.6. Why These Five Trends Matter for AI

These five trends represent distinct but complementary theoretical developments in strategy. They jointly provide:

- A behavioral lens on cognition and decision-making
- A micro-level lens on individuals and interactions
- A system-level lens on ecosystems and platforms
- A stakeholder lens on value creation and claims
- A practice-based lens on strategizing-in-action

Together, they enable a multilayered understanding of strategic management, one that is well-suited to capturing the profound changes introduced by AI. Each trend reveals a different way in which AI destabilizes the assumptions of traditional strategy theories. In subsequent sections, we examine how AI intersects with these areas and how foundational constructs, such as strategic edge, firm boundaries, and the nature of resources, must be reconceptualized in light of AI.

3. How AI Intersects with and Challenges Strategy Theory

AI is not simply a new technology. It is a general-purpose, adaptive, and increasingly agentic system that fundamentally reshapes how firms sense opportunities, make strategic decisions, configure resources, coordinate activities across organizational boundaries, structure network relationships, and ultimately innovate. Unlike prior technologies that automated predefined tasks, AI systems learn, adapt, understand queries and users better, and generate novel solutions, transforming not only the efficiency of strategic processes but the fundamental nature of strategy (Samuel et al. 2022, 2026).

While earlier digital technologies influenced communication, transaction costs, or knowledge flows, AI transforms core strategic mechanisms: sensing, learning, prediction, recombination, attention allocation, and resource deployment. In this section, we show how AI reshapes, extends, and in some cases destabilizes the assumptions embedded in the five theoretical areas outlined earlier. To ground the discussion, we draw upon relevant strategy research, where scholars have begun exploring AI's strategic implications.

3.1. AI and Behavioral Strategy

Behavioral strategy rests on psychological realism, cognition, heuristics, biases, and limited rationality. AI interacts with every part of this foundation, reshaping the informational environment, altering cognitive processes, and introducing a new quasi-agent with its own distinct characteristics.

Below, we highlight four ways in which our theoretical understanding of behavioral strategy is affected by the emergence of strategy in firm practices.

AI alters attention structures and cognitive frames: AI-based systems change how managers perceive and prioritize issues by filtering information (recommender systems, predictive dashboards), by highlighting patterns not readily identifiable by humans, and by structuring interpretive frames through model outputs, confidence scores, or anomaly alerts. [Shrestha et al. \(2019\)](#) show how AI reshapes managerial cognition by augmenting sensemaking processes. AI generates synthetic representations of environments, probability distributions, risk scores, clusters, that serve as cognitive scaffolds, influencing what managers attend to.

AI may attenuate certain biases but amplify others: AI can reduce some biases (anchoring or availability heuristics) by offering more stable baselines or by countering human overconfidence with statistical calibration. Conversely, AI may amplify confirmation bias as humans selectively attend to algorithmic outputs that align with their beliefs. Strategy research on algorithmic decision support ([Ransbotham et al. 2021](#)) warns that humans may overweight algorithmic authority while misunderstanding model error. This raises an important theoretical question: Does AI reduce limited rationality or merely shift its locus?

AI introduces algorithmic biases and model persuasion: AI systems exhibit their own forms of bias, stemming from data sampling, model architectures, or training objectives. These algorithmic biases can shape strategic decisions in ways that differ from human psychological biases but are nonetheless consequential ([Mehrabi et al. 2021](#)). AI may also exhibit persuasive power: the capacity to steer attention, frame options, or nudge decision-makers. As high-stakes strategic decisions become increasingly mediated by AI, behavioral strategy must incorporate human—algorithm joint cognition.

AI changes the emotional landscape of strategizing: Managers may experience anxiety, distrust, or overconfidence in response to AI systems. Emotions influence how they incorporate model outputs and whether they accept or reject AI recommendations. This emotional interface between humans and technology becomes a new determinant of strategic behavior.

3.2. AI and Microfoundations

Microfoundations explain how individual actions produce firm-level outcomes. AI challenges these assumptions by altering the identity of actors, the nature of interactions, and the mechanisms of aggregation and emergence. Below, we highlight three key ways in which the emergence of AI affects our understanding of the microfoundations of strategy.

AI as a strategic actor: Traditional microfoundations assume that individuals are human, cognitively bounded, embedded in social structures, and motivated by incentives, beliefs, and identities. AI violates multiple assumptions simultaneously. It is non human, computationally powerful, trained on large-scale data rather than experiential learning, and motivated (in a sense) only by optimization objectives ([Garvey et al. 2021](#)). These represent fundamental shifts in our understanding of human-non-human interactions within firms. AI becomes a new class of microfoundational actor, neither human nor tool but a hybrid entity performing tasks normally attributed to individuals (forecasting, design, analysis, problem-solving). This challenges the anthropocentric foundations of strategy theory.

AI alters interaction patterns and coordination mechanisms: Human-AI hybrids create new interaction structures. These include delegation chains in which AI performs tasks that humans previously coordinated, predictive coordination, where agents synchronize based on algorithmic forecasts, and hidden interdependencies, because AI models may embed correlations invisible to humans. Strategy research on digital coordination ([von Krogh et al. 2023](#)) provides early insights into how algorithmic systems reshape organizational interactions.

Aggregation dynamics change in human-AI systems: Capabilities arise not simply from human actions but from human-AI co-evolution. Learning loops evolve differently. On one hand, model updates may alter individual behavior, while on the other, individuals fine-tuning models may alter model outputs. This collective behavior feeds new data back into the system. In other words, AI introduces reflexive microfoundations, where emergent outcomes depend on recursive interactions between people and algorithms.

3.3. AI, Ecosystems, and Platforms

AI challenges interconnected network theory at its core. It changes the architecture of complementarities, the nature of multiactor coordination, and the basis of strategic edge. Below, we highlight four ways in which the world of ecosystems and platforms is fundamentally altered by the emergence of AI.

AI increases interconnected network interdependence: Training data, FMs, cloud infrastructures, and application layers form deeply interdependent ecosystems. No single firm controls all necessary components. This aligns with strategy research on interconnected network complexity (Hannah and Eisenhardt 2018), but AI increases interdependence by embedding models into cloud compute layers, data pipelines, development frameworks, and API-based service layers. Such interdependence amplifies both cooperation (shared learning) and competition (model differentiation).

AI contributes to the emergence of FMs: FMs (GPT-like architectures) serve as digital hub cores around which complements, including domain-specific models, datasets, applications, and agentic workflows, develop. Research on digital hub architectures (Kapoor and Agarwal 2017) suggests that core modules determine system evolution. In AI ecosystems, the core becomes updatable, fine-tunable, and partly opaque. This raises new strategic questions: Who owns the model? Who controls training data? Who captures value from downstream complements?

AI reinforces winner-take-most dynamics: AI-driven ecosystems benefit from data network effects, algorithmic feedback loops, scale economies in training, and deployment breadth effects (model quality improves with diverse use cases). Cockburn et al. (2018) show that firms leading in AI enjoy durable performance advantages. These dynamics intensify with FMs, which become increasingly difficult for late entrants to match.

Network governance becomes algorithmic: Governance is increasingly mediated by factors such as model access controls, API pricing, safety constraints, fine-tuning permissions, and bias mitigation protocols (Ustahililoğlu 2025). Interconnected network governance thus becomes model governance, requiring strategy theorists to integrate insights from computer science, ethics, and institutional theory (Rahwan et al. 2019).

3.4. AI and Stakeholder RBV

Stakeholder RBV emphasizes co-created resources and interdependent value. In that respect, it forced us to consider the environment in which organizations operate as the domain of their praxis. AI further reshapes this understanding of the role of stakeholders in a firm. Below, we highlight four ways in which it does so:

Stakeholders generate the most critical resource: Data are the foundation of AI. Yet data originate from stakeholders. Customers generate usage data. Communities generate content data, employees generate operational data, suppliers generate transactional data, regulators generate compliance data, and so forth (Jones and Tonetti 2020). Thus, stakeholder participation becomes integral to AI-related strategic edge. The RBV's traditional assumption that firms own their resources is contradicted by AI, where data sources are shared, contested, or co-created.

Stakeholder power increases with data rights: Stakeholders gain power when they control consent, data access, data deletion rights, and the ability to restrict or condition data sharing. Regulatory bodies also become dominant stakeholders (Constantinides et al. 2018). GDPR, CCPA, and emerging AI-specific regulations redefine property rights over data, shifting power dynamics.

AI generates new stakeholder risks: Stakeholder RBV emphasizes fairness and value distribution. AI creates risks for each stakeholder group (Floridi et al. 2018). Customers face privacy loss and algorithmic discrimination. Workers face automation and deskilling. Communities face surveillance, mis/disinformation, finally, partners face dependency on digital hub-controlled models. The strategic management of stakeholder risks becomes a capability in itself.

Stakeholders participate in AI co-creation: Open-source communities, developers, and crowd workers contribute to training, validating, and fine-tuning models. Value creation becomes multisided, and value appropriation becomes deeply contested (Nambisan et al. 2017).

3.5. AI and SAP

SAP focuses on strategizing as enacted practice, what people do in real situations. AI reshapes the materiality, temporality, and agency of strategizing. Below, we highlight four ways in which it does so.

AI becomes a strategizing tool and companion: AI systems create new strategy tools, including predictive dashboards, text and image generation tools, simulation engines, automated scenario generators, and workflow-oriented agentic systems. Strategizing becomes AI-augmented and, increasingly, AI-shaped.

AI alters the temporal structure of strategizing: Strategy once unfolded in cycles, annual planning, quarterly reviews. AI introduces continuous strategy, through real-time pattern recognition, always-on monitoring, continuous experimentation, and instantaneous simulation. This temporal shift breaks with long-established strategy routines.

AI as a “Quasi-Practitioner”: SAP calls for attention to the practitioners of strategy. AI raises challenging questions: Is AI a strategist? Does it participate in sensemaking? Can it influence agenda-setting? Early theoretical commentary suggests that AI may become a quasi-practitioner, performing tasks traditionally reserved for analysts, consultants, or managers. This expands the ontological boundaries of who participates in strategizing.

AI reshapes meetings, routines, and interactions: Agentic AI tools transcribe meetings, summarize discussions, generate strategic options, and highlight inconsistencies. This changes interaction patterns, power dynamics, what counts as “expertise,” the role of middle managers, and how strategists justify and legitimate decisions (Faraj et al. 2018). These changes affect not just outcomes but the practice of strategy itself.

3.6. Summary

AI intersects with strategy theory in profound ways:

- It alters cognition, attention, bias, and sensemaking.
- It changes microfoundations by introducing nonhuman actors.
- It transforms ecosystems into model-centered, data-driven structures.
- It redefines stakeholder resources and power.
- It reshapes strategizing as an enacted, material practice.

Each theoretical area highlights a different dimension of AI’s transformative power.

In the next segment, we synthesize these insights into a comparative table contrasting pre-AI and post-AI determinants of strategic edge across the five domains.

4. Comparative Framework and Post-AI Transformations

To synthesize the theoretical developments described in earlier sections, this segment presents a comparative table contrasting pre-AI perspectives on the determinants of strategic edge with emerging post-AI perspectives across the five theoretical domains: behavioral strategy, microfoundations, ecosystems and platforms, stakeholder RBV, and SAP. In the following table, we provide an in-depth analytical narrative explaining each transformation and its implications for strategy theory.

Table 1 provides a visual synthesis of the theoretical changes introduced by AI. Figure 1 depicts the impacts of AI on each theoretical domain, with the central role of AI as disruptor, integrator, and change agent driving the transformation from traditional to AI-infused strategic imperatives. Below, we expand on these transformations, explaining how each theoretical area must evolve to capture the mechanisms of advantage in AI-infused organizations and ecosystems.

4.1. Behavioral Strategy: From Human Limited Rationality to Hybrid Cognitive Architectures

Before AI became hegemonic across firms, competitive advantage from a behavioral standpoint hinged on the ability of managers to display heightened cognition, marshal their heuristic judgment, not fall prey to biases, and generally display better judgment at a human level. While these skills are not necessarily neutralized by AI, an additional dimension emerges, that of *human-AI joint cognition*. Attention and sensemaking take on an algorithmic character as well. Below, we highlight three key ways in which a firm’s behavioral strategy is impacted by AI.

From cognitive advantage to hybrid cognitive advantage: Before AI, strategic edge was strongly tied to managerial cognition, how effectively leaders perceived opportunities, interpreted competitive signals, and avoided biases (Kaplan 2008). The behavioral part of strategic edge came from superior attention, superior heuristics, or superior sensemaking.

In the AI era, cognitive advantage is increasingly determined not only by human capabilities but by how firms integrate AI systems into cognitive processes (Jarrahi 2018). AI detects patterns too complex for humans, reallocates attention through alerts, flags, and prioritization, and reframes decision problems via simulations or model-generated alternatives. Strategizing becomes a human–algorithm collaboration, with algorithmic cognition supporting, shaping, or sometimes overriding human judgment (Faraj et al. 2018).

Algorithmic bias as a strategic variable: Where behavioral strategy once emphasized human biases, firms must now manage human biases, algorithmic biases, and biases emerging from human–algorithm interaction loops.

Table 1: Pre-AI and post-AI perspectives on determinants of competitive advantage.

Theory	Pre-AI Perspective	Post-AI Perspective
Behavioral Strategy	Advantage hinges on superior managerial cognition, effective heuristics, reduced biases, and high-quality executive judgment. Strategic outcomes depend on how managers interpret environments.	Advantage depends on <i>human–AI joint cognition</i> , algorithmic augmentation of attention and sensemaking, the governance of model biases, and firms’ ability to integrate algorithmic and human judgment. Strategic outcomes reflect hybrid cognitive architectures.
Microfoundations	Firm-level capabilities and performance arise from individual-level skills, interactions, motivations, and emergent routines. All microfoundations are human.	Capabilities arise from <i>sociotechnical ensembles</i> of humans and AI systems. AI functions as a quasi-actor embedded in routines, altering interaction patterns, delegation structures, and emergent dynamics. Microfoundations include algorithmic agents.
Ecosystems and Platforms	Advantage emerges through complementarities, control of platform architectures, network effects, and superior governance of multiactor systems.	Advantage emerges from control of <i>AI foundation models</i> , data ecosystems, compute resources, and model governance. Ecosystems become model-centric; competition shifts to learning loops, fine-tuning networks, and AI capability diffusion.
Stakeholder RBV	Stakeholders contribute unique resources (knowledge, legitimacy, relationships), but firms primarily control and appropriate resources. Value creation occurs in firm-stakeholder relationships.	Stakeholders generate and control critical AI resources (data, feedback, content). Advantage depends on fair governance of data rights, ethical AI practices, stakeholder trust, and <i>co-creation</i> in model training and validation. Stakeholder power increases.
Strategy-as-Practice (SAP)	Strategy emerges through human practices: meetings, analyses, interpretations, routines, and tools shaping the everyday doing of strategy.	Strategy emerges through <i>AI-augmented practices</i> : automated analyses, AI-generated insights, simulations, and agentic workflows. AI becomes a quasi-practitioner influencing routines, interpretations, and power dynamics.

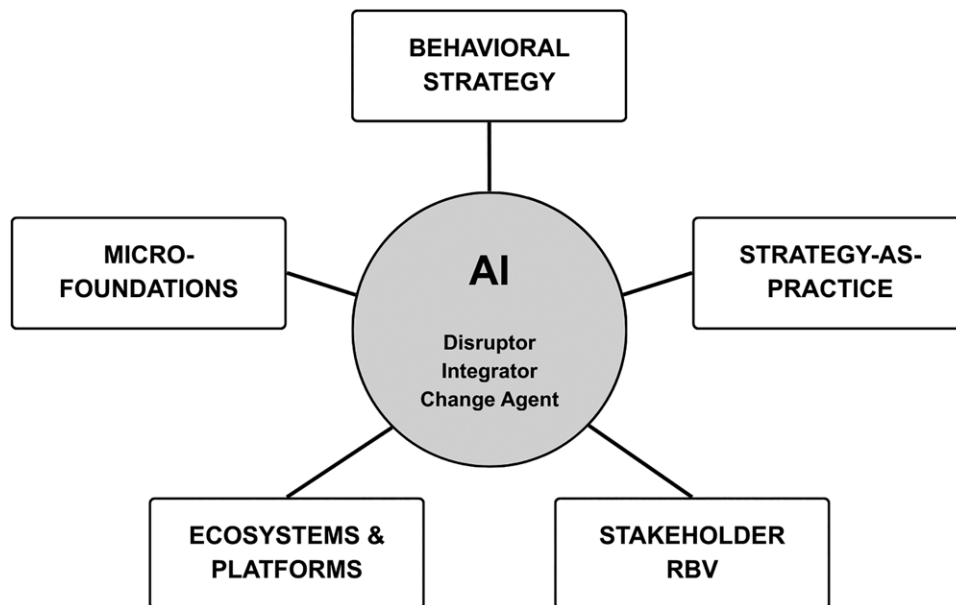


Figure 1: Strategy imperatives impacted by AI.

Strategic edge may depend on how well firms mitigate and harness these biases (Barocas and Selbst 2016; Jarrahi 2018).

Strategic emotion in human-AI interaction: Trust, anxiety, and overreliance on algorithms become emotional factors shaping strategy (Dietvorst et al. 2015). Organizations that manage emotional adaptation to AI (through training, transparency, or governance) outperform those that struggle with AI-induced discomfort or resistance (Glikson and Woolley 2020).

Table 2 synthesizes how AI transforms behavioral strategy across three dimensions. Human cognition evolves into hybrid cognition where algorithmic systems augment managerial sensemaking through pattern detection and cognitive scaffolds. Heuristics and biases expand to include managing both human and algorithmic biases, raising the question of whether AI reduces bounded rationality or merely shifts its locus. Limited rationality gives way to an emotional landscape where trust, anxiety, and adaptation to AI systems become strategic determinants.

These transformations reveal that cognitive advantage now depends on how effectively firms integrate algorithmic and human judgment while managing the emotional interface between humans and technology.

4.2. Microfoundations: From Human Capabilities to Sociotechnical Capabilities

As Table 1 suggests, microfoundations in the pre-AI era were predicated upon individual-level skills, interactions, motivations, and emergent routines. It was a *sine qua non* that all microfoundations were human. The terrain has shifted considerably in the post-AI era. Microfoundations now necessarily include algorithmic agents. Agentic AI gives rise to quasi-actors embedded in routines. They function to transform interaction patterns, disrupt delegation structures, and reconfigure emergent dynamics for better or for worse. Below, we highlight three ways in which the terrain of microfoundations has been transformed by AI.

AI as a microfoundational actor: Microfoundations theory must expand its ontology. Pre-AI microfoundations were explicitly human: individuals, their skills, their interactions. Post-AI, many traditionally human tasks, forecasting, classification, text generation, diagnosis, resource allocation, are performed by AI systems (Raisch and Krakowski 2021). This generates hybrid microfoundations, comprising humans, algorithms, interaction rules, data flows, and feedback loops. New “individual-level” heterogeneity emerges from differences in model architectures, training regimes, and fine-tuning (Felin et al. 2015).

Changing interaction patterns: Human-AI collaboration introduces new forms of coordination. These include algorithm-mediated coordination (AI recommends who should do what), predictive synchronization (AI predicts others’ actions and informs teammates), and multiagent interactions (multiple AI agents interacting with humans). Capabilities emerge from interdependencies across human and algorithmic nodes.

Emergence in hybrid systems: Classic emergence involved repeated human interaction. Post-AI emergence depends on model updates, data drift, reinforcement learning feedback, and human adaptation to algorithmic cues. The locus of emergence shifts toward dynamic human–AI co-evolution (Murray et al. 2021; Shrestha et al. 2021).

AI necessitates attention to the transformation of microfoundations from purely human actors to sociotechnical capabilities. Individual capabilities must expand to include AI systems performing traditionally human tasks (forecasting, classification, text generation), generating hybrid microfoundations comprising humans, algorithms, and data flows (see Table 3).

Human interactions can be transformed into algorithm-mediated coordination where AIs can be deployed to recommend task allocation, enables predictive synchronization, and create multiagent interactions. Skill-based heterogeneity would yield to adaptivity through continuous reconfiguration (Felin et al. 2015), where competitive advantage stems from real-time adjustment rather than accumulated knowledge stocks (Teece 2018). These changes will fundamentally alter how firm-level outcomes emerge from individual-level actions and shift the locus of emergence toward dynamic human-AI co-evolution.

4.3. Ecosystems and Platforms: From Modular to Model-Centric

In the 21st century, platforms began to replace products as a source of competitive advantage in diversified firms, especially in the space of technology-enabled commerce. It was believed that competitive advantage emerged in these platforms through complementarities, control of platform architectures, network effects, and superior governance of multiactor systems. All those determinants of performance differentials remain salient, but a new layer emerges in the post-AI landscape. The new source of competitive advantage is AI FMs, data ecosystems (Iansiti and Lakhani 2020), compute resources, and model governance (Schrepel and Pentland 2025). The model becomes

Table 2: Behavioral strategy: Pre-AI to post-AI transformation.

Pre-AI Theoretical Dimension	Post-AI Theoretical Dimension(s)	Transformation Description	Key Mechanisms	Research Implications
<p>Human Cognition Strategic edge tied to managerial cognition, how effectively leaders perceived opportunities, interpreted competitive signals, and avoided biases (Gavetti 2005; Gary and Wood 2011; Eggers and Kaplan 2013; Kaplan 2011).</p> <p>Heuristics and Biases Strategic choices shaped by psychological biases (overconfidence, loss aversion, anchoring, escalation of commitment). Heuristics sometimes facilitate strategizing by simplifying complexity (Powell et al. 2011).</p> <p>Limited Rationality Behavioral strategy assumes bounded, structured, and socially embedded rationality rather than perfect rationality (Simon 1947; Cyert and March 1963).</p>	<p>Hybrid Cognition Cognitive advantage determined by how firms integrate AI systems into cognitive processes. AI detects patterns too complex for humans, real-locates attention, and reframes decision problems (Shrestha et al. 2019).</p> <p>Algorithmic Biases Firms must manage human biases, algorithmic biases, and biases emerging from human-algorithm interaction loops. AI may reduce some biases but amplify others (Ransbotham et al. 2017).</p> <p>Emotional Landscape of Strategizing Trust, anxiety, and overreliance on algorithms become emotional factors shaping strategy. Organizations that manage emotional adaptation to AI outperform those struggling with AI-induced discomfort (McDonald and Westphal 2013).</p>	<p>Strategizing becomes a human-algorithm collaboration, with algorithmic cognition supporting, shaping, or sometimes overriding human judgment.</p> <p>Strategic edge depends on how well firms mitigate and harness biases. Raises question: Does AI reduce limited rationality or merely shift its locus?</p> <p>Emotional interface between humans and technology becomes a new determinant of strategic behavior through training, transparency, or governance.</p>	<ul style="list-style-type: none"> • Recommender systems, predictive dashboards • Filtering information • Cognitive scaffolds • Alerts, flags, prioritization • Statistical calibration • Confirmation bias amplification • Algorithmic authority • Data sampling biases • Manager anxiety, distrust • Overconfidence responses • Training, transparency • Governance mechanisms 	<p>Research should examine how AI augmentation affects managerial mental models, decision heuristics, and strategic frames (Riedl et al. 2024). How do firms integrate algorithmic and human judgment into cognitive processes? What governance mechanisms manage emotional adaptation to AI?</p> <p>Under what conditions does AI amplify versus mitigate cognitive biases? (Kahneman and Klein 2009) How do firms manage human biases, algorithmic biases, and interaction loop biases?*</p> <p>How do managers calibrate trust in algorithmic versus human judgment? What organizational practices facilitate emotional adaptation to AI?*</p>

*Theorized in this paper.

Table 3: Microfoundations: Pre-AI to post-AI transformation.

Pre-AI Theoretical Dimension	Post-AI Theoretical Dimension(s)	Transformation Description	Key Mechanisms	Research Implications
<p>Individual Capabilities Microfoundations were explicitly human: individuals, their skills, their interactions. Capabilities and routines originate from skills, motivations, knowledge, and cognitive differences among individuals (Felin and Foss 2005; Felin et al. 2015; Barney and Felin 2013).</p>	<p>Sociotechnical Capabilities Many traditionally human tasks (forecasting, classification, text generation, diagnosis, resource allocation) are performed by AI systems. This generates hybrid microfoundations, comprising humans, algorithms, interaction rules, data flows, and feedback loops.</p>	<p>Microfoundations theory must expand its ontology. New individual-level heterogeneity emerges from differences in model architectures, training regimes, and fine-tuning quality.</p>	<ul style="list-style-type: none"> AI performing human tasks Hybrid microfoundations Model architectures Training regimes, fine-tuning 	<p>Future research must theorize how agency is distributed across human-AI ensembles, drawing on actor-network theory (Latour 2005; Callon 1984), distributed cognition frameworks, and computational organizational theory. Under what conditions do algorithmic agents complement versus substitute for human judgment? How do power dynamics shift when AI systems mediate strategic decisions?*</p>
<p>Human Interactions Organizational outcomes arise through structured human interactions supported by coordination mechanisms, relational contracts, communication patterns, and shared understandings (Felin et al. 2015).</p>	<p>Human-AI Coordination Human-AI collaboration introduces new forms of coordination: algorithm-mediated coordination, predictive synchronization, and multiagent interactions. Capabilities emerge from interdependencies across human and algorithmic nodes (von Krogh et al. 2023).</p>	<p>Agentic AI gives rise to quasi-actors embedded in routines. They function to transform interaction patterns, disrupt delegation structures, and reconfigure emergent dynamics.</p>	<ul style="list-style-type: none"> Algorithm-mediated coordination Predictive synchronization Multiagent interactions Quasi-actors in routines 	<p>Future work should integrate insights from human-computer interaction (Sidji et al. 2024), cognitive science, and behavioral decision theory. What coordination mechanisms enable effective human-AI collaboration at scale? What new governance forms emerge when responsibility is distributed between humans and machines?*</p>
<p>Skill-Based Heterogeneity Individual-level heterogeneity in skills creates firm-level capability differences. Competitive advantage stems from learning capability, the ability to accumulate, codify, and leverage knowledge over time (Teecle et al. 1997; Eisenhardt and Martin 2000).</p>	<p>Adaptivity through Continuous Reconfiguration Advantage shifts toward adaptivity, the capacity to continuously reconfigure in response to real-time feedback. AI systems enable this through continuous sensing, pattern recognition, and adjustment rather than episodic learning cycles (Winter 2003; Zollo and Winter 2002).</p>	<p>Post-AI emergence depends on model updates, data drift, reinforcement learning feedback, and human adaptation to algorithmic cues. The locus of emergence shifts toward dynamic human-AI co-evolution.</p>	<ul style="list-style-type: none"> Model updates Data drift Reinforcement learning feedback Human-AI co-evolution 	<p>What organizational structures enable continuous adaptivity rather than episodic learning cycles? How do firms build adaptive capacity without sacrificing stability required for operational effectiveness? What governance mechanisms ensure adaptive systems remain aligned with strategic intent?*</p>

*Theorized in this paper.

salient to the ecosystem and AI capability diffusion becomes key. Below, we highlight four key elements of that transformation.

FMs become the new digital hub cores: Historically, platforms coordinated complementarities (apps, suppliers, modules). With AI, FMs become the core modules of ecosystems, generating capabilities across domains (language, vision, code), lowering the cost of complement creation (agents, apps, copilots), and serving as focal points for innovation communities (Bommasani et al. 2021; Bresnahan and Greenstein 1999). Innovation in FM-centric ecosystems emerges through two mechanisms: *emergent capability discovery*, where developers uncover unanticipated problem-solving abilities (such as cross-domain reasoning or novel task performance) that enable applications not envisioned during model development, and *architectural homogenization*, where standardized FM interfaces allow rapid deployment across diverse sectors with minimal adaptation (Bresnahan and Trajtenberg 1995; Baldwin and Clark 2000). For example, a breakthrough in legal document analysis can immediately inform medical diagnosis, customer service, or software development applications. Control over FMs thus becomes a primary source of interconnected network power, as these dual innovation mechanisms create network effects that reinforce the centrality of dominant models.

AI amplifies winner-take-most competition: FM ecosystems fundamentally reshape competitive dynamics by introducing self-reinforcing learning advantages. Model quality compounds over time through more data, larger user bases, more diverse fine-tuning tasks, and network effects from shared model improvements. This creates *learning-based strategic edges* that differ fundamentally from traditional network effects. While conventional network effects increase value through adoption, learning-based advantages improve the core product itself. Each interaction generates training data that enhance model performance, attracting more users and generating more data in a compounding cycle. Laggards face increasingly insurmountable barriers because catching up requires not just matching current capabilities but replicating the cumulative learning embedded in leaders' models (Agarwal et al. 2022). Competition thus shifts from contestable markets where late entrants can leapfrog incumbents, to cumulative-advantage markets where early leaders' learning curves create persistent performance gaps that challenge traditional strategy assumptions about competitive mobility.

Ecosystem governance becomes technical: Governance shifts from managing human complementarities to managing model access and API-based rules (Gillespie 2014). These include rate limits, safety constraints, fine-tuning permissions, model versioning, and compliance requirements. Firms with superior model governance architectures (transparent, safe, flexible) outperform on interconnected network health. Critically, governance decisions become *encoded in technical infrastructure* rather than negotiated through contracts or social norms. Access controls, usage policies, and quality standards are embedded directly into APIs, creating quasi-regulatory systems that shape complementor behavior automatically (Plantin et al. 2018). This technical embedding of governance rules accelerates enforcement but also raises new strategic questions about who designs these architectures, how power is distributed across governance layers, and whether complementors can effectively contest or exit from technically-mediated systems.

Multi-interconnected network intensifies interdependence: AI models depend on global data sources, interoperable tools, and cross-ecosystem infrastructures (Tilson et al. 2010; Yoo et al. 2010). Firms compete not just as stand-alone platforms but as interdependent ecosystems, where one ecosystem's model may rely on another's compute layer, while complementors cross-deploy applications across model ecosystems and industry boundaries blur around cross-model interoperability. The ecosystem becomes the key unit of analysis, yet traditional ecosystem theory assumes relatively stable boundaries and clear hierarchies. AI ecosystems exhibit *fluid boundaries* where participants simultaneously cooperate (sharing infrastructure, data standards, pre-trained models) and compete (differentiating on fine-tuning, application layers, user relationships), creating co-competition dynamics that are more complex and dynamic than platform-era competition (Klinger et al. 2020). Strategic advantage increasingly depends on orchestrating relationships across multiple, overlapping ecosystems rather than dominating a single, bounded platform.

In summary, AI will drive the transformation of ecosystems and platforms from modular architectures to model-centric structures (see Table 4).

FMs will replace traditional platform cores, generating capabilities across domains and lowering creation costs through emergent capabilities and architectural homogenization. Platform coordination will evolve into technically-mediated governance where API-based rules, access controls, and quality standards are embedded directly into the infrastructure, creating quasi-regulatory systems (Jacobides et al. 2019). We anticipate that traditional network effects will give way to learning-based strategic edges where model quality compounds through self-reinforcing data cycles, creating cumulative advantages and persistent performance gaps for early leaders. As a result, competition will shift from contestable markets to overlapping ecosystems where participants simultaneously cooperate and compete through shared infrastructure and cross-model interoperability.

Table 4: Ecosystems and platforms: Pre-AI to post-AI transformation.

Pre-AI Theoretical Dimension	Post-AI Theoretical Dimension(s)	Transformation Description	Key Mechanisms	Research Implications
<p>Modular Complementarities Platforms coordinated complementarities (apps, suppliers, modules). Competitive advantage emerged through complementarities, control of platform architectures, network effects, and superior governance of multiactor systems (Hannah and Eisenhardt 2018; Kapoor and Agarwal 2017).</p>	<p>Foundation Models as Digital Hub Cores Foundation models become core modules of ecosystems, generating capabilities across domains (language, vision, code), lowering the cost of complement creation (agents, apps, copilots), and serving as focal points for innovation communities.</p>	<p>Control over foundation models becomes a primary source of interconnected network power. Innovation emerges through emergent capability discovery and architectural homogenization.</p>	<ul style="list-style-type: none"> • Foundation models (FMs) • Emergent capability discovery • Architectural homogenization • Standardized FM interfaces 	<p>How do firms orchestrate multi-actor learning systems? (Hannah and Eisenhardt 2018) Future work should integrate ecosystem theory (Adner and Kapoor 2010) with research on open innovation (Chesbrough 2003), standards competition, and collective intelligence. What governance mechanisms align incentives when value creation depends on shared data and models?*</p>
<p>Platform Coordination Governance managed human complementarities through contracts and social norms. Platforms coordinated value creation across multiple firms with relatively stable boundaries and clear hierarchies.</p>	<p>Model-Centric Ecosystems with Technical Governance Governance shifts to managing model access and API-based rules. Governance decisions become encoded in technical infrastructure rather than negotiated. Access controls, usage policies, and quality standards are embedded directly into APIs (Xu et al. 2025).</p>	<p>AI ecosystems exhibit fluid boundaries where participants simultaneously cooperate (sharing infrastructure, data standards, pre-trained models) and compete (differentiating on fine-tuning, application layers, user relationships).</p>	<ul style="list-style-type: none"> • API-based rules • Rate limits, safety constraints • Fine-tuning permissions • Quasi-regulatory systems 	<p>In AI ecosystems, each participant's interactions generate data that improves a shared foundation model, creating knowledge spillovers that benefit all members including competitors (Khan et al. 2024). How is power distributed across governance layers in technically-mediated systems?*</p> <p>Can complementors effectively contest or exit from technically-mediated systems?*</p>

Table 4: (continued)—Ecosystems and platforms: Pre-AI to post-AI transformation.

Pre-AI Theoretical Dimension	Post-AI Theoretical Dimension(s)	Transformation Description	Key Mechanisms	Research Implications
Learning-Based Strategic Edges				
Network Effects Traditional network effects increase value through adoption. Competition occurred in contestable markets where late entrants could leapfrog incumbents.	Model quality compounds over time through more data, larger user bases, more diverse fine-tuning tasks, and network effects from shared model improvements. Learning-based advantages improve the core product itself. Each interaction generates training data that enhances model performance (Cockburn et al. 2018).	Competition shifts from contestable markets to cumulative-advantage markets where early leaders' learning curves create persistent performance gaps. Laggards face insurmountable barriers because catching up requires replicating cumulative learning embedded in leaders' models.	<ul style="list-style-type: none"> • Self-reinforcing learning • Training data enhancement • Compounding cycle • Cumulative learning barriers 	How do firms compete in cumulative-advantage markets where early leaders' learning curves create persistent performance gaps? What strategies enable laggards to overcome cumulative learning barriers? How does strategic advantage depend on orchestrating relationships across multiple, overlapping ecosystems?

*Theorized in this paper.

4.4. Stakeholder RBV: From Firm-Controlled Resources to Stakeholder-Governed Data and Trust

Stakeholders were always considered key to a firm's competitive advantage, but it was felt that they did so by contributing unique resources (knowledge, legitimacy, relationships). Despite their salience, it was believed that the primary firms controlled and appropriated resources (Hillman and Keim 2001). Things have transformed rather radically in this realm. In the post-AI landscape, stakeholders generate and control critical AI resources (data, feedback, content). The gains therefrom will have to be shared as their power increases. Moreover, competitive advantage is predicated upon the on fair sharing of data rights. Below, we highlight four themes relating to the transformation of firm-stakeholder relationships in the post-AI era.

Stakeholders own or control critical inputs: The most important AI resource, data, originates with stakeholders. This reverses the logic of resource control. Before AI became hegemonic, firms owned their resources (factories, IP, proprietary routines). In the post-AI world of firms, stakeholders generate the key resource (data), and firms must govern access and use responsibly (Zuboff 2019; Khatri and Brown 2010). This creates a new basis for advantage: trusted access to stakeholder-generated resources.

Data rights become strategic assets: Data protection laws, consent frameworks, and community norms shape what data firms can use, how they can use it, and whether stakeholders will cooperate with them over the short and long term. Firms with stronger reputations for fairness, privacy, transparency, and reciprocity gain a long-term resource advantage.

Stakeholder risks become strategic constraints: Stakeholders may resist AI adoption for a variety of reasons, including privacy fears, AI phobia, job displacement, and algorithmic unfairness (Samuel et al. 2025). Managing stakeholder risks is no longer just CSR, it becomes a capability that determines whether firms can sustain AI-driven advantage.

Stakeholders become co-developers of capabilities: In the AI era, it becomes imperative for firms to partner with their stakeholders through feedback, ratings, content creation, fine-tuning interactions, and crowdsourced testing. Stakeholders help develop and refine AI capabilities. Firms cannot monopolize value; they must orchestrate co-creation (Pralhad and Ramaswamy 2004; Laursen and Salter 2006).

We predict that stakeholder RBV will evolve from firm-controlled resources to stakeholder-governed data ecosystems. The most critical AI resource, data, originates with stakeholders, reversing traditional resource control logic and creating new bases for advantage through trusted access (see Table 5).

Data rights will serve as strategic assets, and protection laws, consent frameworks, and community norms will shape what firms can use and whether stakeholders cooperate. As a result, resource creation will shift from firm-directed processes to co-creation opportunities where firms partner with stakeholders through feedback, ratings, content creation, and crowdsourced testing. Managing stakeholder risks around privacy, displacement, and algorithmic fairness will become a capability that determines whether firms can sustain AI-driven advantages.

4.5. SAP: From Human Strategizing to AI-Augmented Strategizing

As Table 1 suggests, our pre-AI concepts of strategizing primarily involved human practices. Transforming strategy work into a verb involved meetings, analyses, artifacts like documents and spreadsheets, and routines that highlighted the performative elements of strategy. Things are a bit different in the post-AI landscape. Today, the "verbing" of strategy includes AI-augmented practices. These include automated analyses, AI-generated insights, simulations, and agent powered workflows. AI becomes a quasi-practitioner influencing routines, interpretations, and power dynamics (Jarzabkowski and Kaplan 2015). Below, we highlight four ways in which SAP has been transformed by AI.

AI becomes a ubiquitous strategy tool: Strategizing becomes materially transformed, through real-time dashboards replacing periodic reports, generative AI producing draft strategic alternatives, simulation engines evaluating competitive moves, and agentic AI conducting environmental scanning automatically. These practices change not only outputs but how strategists act.

AI changes the rhythm of strategy work: Strategy becomes dynamic and continuous, requiring always-on monitoring, instant experimentation, automated scenario testing, and continuous learning loops (Faraj et al. 2018; Raisch and Krakowski 2021). This contrasts sharply with pre-AI episodic planning.

AI as a quasi-practitioner: AI joins the cast of strategists. It participates in meetings through summaries and insights, produces analytic content, flags risks and opportunities, and sometimes even initiates strategic options (Jarzabkowski and Kaplan 2015). This raises new questions about who "owns" strategic decisions, how credit or accountability should be assigned, and what becomes of expertise when AI can generate equivalent outputs.

Table 5: Stakeholder RBV: Pre-AI to post-AI transformation.

Pre-AI Theoretical Dimension	Post-AI Theoretical Dimension(s)	Transformation Description	Key Mechanisms	Research Implications
Firm-controlled Resources				
Stakeholders contributed unique resources (knowledge, legitimacy, relationships). Primary firms controlled and appropriated resources (factories, IP, proprietary routines).	Stakeholder-Generated Data The most important AI resource, data, originates with stakeholders. This reverses the logic of resource control. Stakeholders generate the key resource (data), and firms must govern access and use responsibly (Freeman 1984; Freeman et al. 2007).	Creates a new basis for advantage: trusted access to stakeholder-generated resources. Competitive advantage is predicated upon fair sharing of data rights.	<ul style="list-style-type: none"> Stakeholder data generation Reversed resource control logic Responsible governance Trusted access 	How should firms balance value appropriation with fair treatment of stakeholders who provide training data? Research should examine questions of algorithmic justice (Mittelstadt et al. 2016), data rights, and stakeholder voice in AI governance (Floridi et al. 2018). What accountability mechanisms ensure AI systems respect stakeholder interests? (Diakopoulos 2016)
Stakeholder Contributions				
Stakeholders contributed resources but had limited power over resource use and value appropriation. Firms primarily controlled strategic decisions about resource deployment.	Data Rights as Strategic Assets Data protection laws, consent frameworks, and community norms shape what data firms can use and whether stakeholders will cooperate. Firms with stronger reputations for fairness, privacy, transparency, and reciprocity gain long-term resource advantage.	Stakeholders gain power when they control consent, data access, data deletion rights, and ability to restrict or condition data sharing. Regulatory bodies become dominant stakeholders.	<ul style="list-style-type: none"> Data protection laws Consent frameworks Fairness, privacy, transparency Regulatory power 	How do power asymmetries shift when firms control algorithms mediating stakeholder interactions? How do data rights and consent frameworks reshape competitive dynamics? What mechanisms enable stakeholders to exercise voice in AI governance?
Resource Creation				
Firms created and controlled resources. Stakeholders provided inputs but firms determined resource use and captured most value. Resource creation was largely firm-directed.	Co-Creation and Ethical Governance Firms partner with stakeholders through feedback, ratings, content creation, fine-tuning interactions, and crowdsourced testing. Stakeholders help develop and refine AI capabilities. Firms cannot monopolize value and must orchestrate co-creation.	Managing stakeholder risks (privacy fears, job displacement, algorithmic unfairness) becomes a capability that determines whether firms can sustain AI-driven advantage. Value creation becomes multilateral and value appropriation becomes deeply contested.	<ul style="list-style-type: none"> Feedback, ratings Content creation Fine-tuning interactions Crowdsourced testing 	How do firms orchestrate value co-creation with stakeholders in AI development? What governance structures enable fair value appropriation across stakeholder groups? How do firms manage stakeholder risks (privacy, displacement, unfairness) as strategic capabilities?

*Theorized in this paper.

Power dynamics shift within strategizing groups: AI redistributes power by empowering junior analysts with sophisticated analysis tools, reducing reliance on experience-based intuition, shifting influence toward those who understand AI systems, and altering the expertise hierarchy. The practice of strategy becomes a negotiation between human expertise, algorithmic suggestions, and institutional expectations (Christin 2020).

In short, SAP will transform from episodic planning to continuous, AI-augmented strategizing (see Table 6).

The temporal rhythm will shift from periodic reviews and annual planning cycles to constant monitoring, instant experimentation, and continuous learning loops enabled by real-time dashboards. Consequently, AI-augmented practices where automated analyses, generative AI, simulation engines, and agentic workflows will materially transform how strategy is performed (Faraj et al. 2018; Raisch and Krakowski 2021). We also predict a shift in power dynamics when AI redistributes influence by empowering junior analysts with sophisticated tools (Raisch and Krakowski 2021), reducing reliance on experience-based intuition (Faraj et al. 2018), and altering expertise hierarchies by democratizing access to *technologies of rationality* (Jarzabkowski and Kaplan 2015). AI will join the cast of strategists as a quasi-practitioner, participating through summaries, producing analytic content, and flagging opportunities (Orlikowski and Scott 2008; Raisch and Krakowski 2021). This raises fundamental questions about who owns strategic decisions and what constitutes expertise when AI can generate equivalent outputs (Faraj et al. 2018)

4.6. A New Architecture of Strategic Edge: Individual, Firm, and Ecosystem Transformations

Across all five theoretical areas, AI has introduced a paradigm shift. Cognition has become hybrid, capabilities have become sociotechnical, ecosystems have become model-centric, resources have become stakeholder-generated, and strategizing has become AI-augmented. Traditional sources of advantage, economies of scale, cost leadership, differentiation, resource uniqueness—remain relevant but are increasingly overshadowed by learning-based advantages, data network effects, model governance capabilities, hybrid cognitive systems, and ecosystem orchestration skills.

AI functions simultaneously as disruptor, integrator, and change agent. As a disruptor, AI upends established business models and competitive positions through rapid capability advancement and unpredictable emergent behaviors (Christensen et al. 2015). As an integrator, AI's architectural homogeneity in FMs enables the combination of value creation activities across previously disconnected domains, while its probabilistic reasoning and generative capabilities provide normative guidance that reshapes decision processes and substitutes for human labor. As a change agent, AI's accelerating development since 2022 has compressed timescales for strategic adaptation, forcing organizations to respond to technological shifts that once unfolded over decades.

Building on these roles and the theoretical transformations outlined above, we define AI in strategic management terms as: *an adaptive general-purpose transformative system with powerful but incomplete capabilities in cognition, learning, and creativity that fundamentally reshapes how firms sense opportunities, make decisions, configure resources, coordinate activities, and innovate.* This new perspective necessitates expansions to established strategy frameworks and the development of new theoretical constructs. Our definition emphasizes not only what AI is ontologically, but what AI does strategically. It transforms the mechanisms through which competitive advantage is created, sustained, and appropriated. AI does not simply modify strategy theory; it rewrites it.

While the five theoretical perspectives examined above illuminate distinct facets of AI's impact on strategy, they collectively reveal a deeper multilevel architecture of transformation. AI does not simply alter individual theories in isolation; rather, it operates simultaneously across three fundamental levels of strategic analysis: individual cognition, firm-level capabilities, and ecosystem-level coordination. These levels are interconnected through cascading effects and feedback loops that amplify AI's transformative power.

At the individual level, AI fundamentally reshapes managerial cognition. Traditional strategy scholarship has long emphasized bounded rationality, cognitive biases, and limited information processing capacity as constraints on strategic decision-making (Simon 1947; Kahneman and Klein 2009; Gavetti and Levinthal 2000). AI introduces cognitive augmentation mechanisms including algorithmic decision support (Shrestha et al. 2021), distributed cognition systems (Riedl et al. 2024), and hybrid problem-solving capabilities (Raisch and Fomina 2025; Passerini et al. 2025) that transform individual cognition into hybrid human-AI architectures (Jarrahi 2018; Murray et al. 2021). Managers need no longer be bounded by the confines of their biological cognitive limitations. Instead, they can rely on AI-augmented judgment, enhanced information processing (Samuel et al. 2022), and complementary human-AI capabilities (Raisch and Krakowski 2021) that create new forms of causal reasoning and expertise (Glikson and Woolley 2020). This shift from bounded rationality to hybrid cognition represents a fundamental change in the microfoundations of strategic behavior (Eggers and Kaplan 2013; Gavetti 2012).

At the firm level, AI can transform the nature of competitive advantage. In the past competitive advantages were the result of differences in valuable, rare, inimitable, and non-substitutable resources. These were complemented by

Table 6: Strategy-as-practice: Pre-AI to post-AI transformation.

Pre-AI Theoretical Dimension	Post-AI Theoretical Dimension(s)	Transformation Description	Key Mechanisms	Research Implications
<p>Episodic Planning Strategy unfolded in cycles through periodic reports, annual planning, and quarterly reviews. Human strategists conducted analyses using artifacts like documents and spreadsheets (Whittington 2006; Jarzabkowski and Spee 2009).</p>	<p>Continuous Strategy Strategy becomes dynamic and continuous, requiring always-on monitoring, instant experimentation, automated scenario testing, and continuous learning loops. Real-time dashboards replace periodic reports.</p>	<p>AI changes the rhythm of strategy work. This temporal shift breaks with long-established strategy routines, contrasting sharply with pre-AI episodic planning.</p>	<ul style="list-style-type: none"> • Real-time dashboards • Always-on monitoring • Instant experimentation • Continuous learning loops 	<p>How does AI change micro-level practices of strategizing (meetings, planning cycles, decision routines)? (Jarzabkowski and Spee 2009; Whittington 2006) What new forms of strategizing emerge when AI enables real-time scenario analysis? * Future work should employ ethnographic methods, practice theory, and sociomateriality frameworks (Orlikowski 2007; Leonardi 2011).</p>
<p>Human Strategists Strategizing involved human practices through meetings, analyses, and routines that highlighted performative elements of strategy. Strategists included top managers, middle managers, consultants, and analysts.</p>	<p>AI-Augmented Practices Strategizing becomes materially transformed through automated analyses, AI-generated insights, simulations, and agent-powered workflows. Generative AI produces draft strategic alternatives, simulation engines evaluate competitive moves, and agentic AI conducts environmental scanning automatically.</p>	<p>AI becomes a ubiquitous strategy tool. These practices change not only outputs but how strategists act.</p>	<ul style="list-style-type: none"> • Automated analyses • AI-generated insights • Simulation engines • Agentic AI workflows 	<p>How can practitioners navigate tensions between algorithmic recommendations and experiential judgment? * How do AI-augmented practices change the material and temporal structure of strategizing? * What role does AI play as a quasi-practitioner in strategic decision-making? *</p>
<p>Periodic Reviews Strategy work followed established hierarchies where expertise came from experience. Power derived from knowledge accumulation and senior position in organizational hierarchy.</p>	<p>Real-Time Adaptation AI redistributes power by empowering junior analysts with sophisticated analysis tools, reducing reliance on experience-based intuition, shifting influence toward those who understand AI systems, and altering the expertise hierarchy. AI participates in meetings through summaries and insights, produces analytic content, and flags risks and opportunities.</p>	<p>Power dynamics shift within strategizing groups. The practice of strategy becomes a negotiation between human expertise, algorithmic suggestions, and institutional expectations. Raises questions about who owns strategic decisions and how credit or accountability should be assigned.</p>	<ul style="list-style-type: none"> • Empowering junior analysts • Reducing experience-based intuition • AI system understanding • Altered expertise hierarchy 	<p>How do power dynamics shift when AI systems participate in strategic decision-making? * Who owns strategic decisions when AI initiates strategic options? * What becomes of expertise when AI can generate equivalent outputs? *</p>

*Theorized in this paper.

organizational capabilities, routines, and hierarchical coordination within clearly defined firm boundaries (Barney 1991; Teece et al. 1997). AI introduces opportunities for data accumulation, algorithmic capability building, socio-technical integration, and dynamic reconfiguration that can shift the basis of advantage from resource stocks to learning velocities (Agarwal et al. 2022; Iansiti and Lakhani 2020; Raisch and Krakowski 2021). Post-AI competitive advantage will depend on learning-based advantages, sociotechnical capabilities that blend human and algorithmic actors, human-AI collaborative routines, porous organizational boundaries, and fluid, AI-enabled coordination structures (Faraj et al. 2018; Orlikowski and Scott 2008; Raisch and Fomina 2025). Firms will no longer compete primarily on what they own, but on how rapidly they learn.

At the ecosystem level, AI can reconfigure the locus and logic of competition. Traditional ecosystem theories emphasized network effects, modular architectures, platform governance, and complementary relationships within relatively stable value creation structures (Jacobides et al. 2018; Adner 2017). AI introduces FMs as organizing hubs, data ecosystems as competitive arenas, cross-platform learning as a source of spillovers, and AI-driven orchestration mechanisms as enablers of continuous co-evolution (Bommasani et al. 2021; Schrepel and Pentland 2025; Xu et al. 2025). The result is a shift toward model-centric ecosystems where advantage will accrue to those who control FMs, leverage data network effects, manage AI-driven complementarities, orchestrate distributed intelligence, and participate in dynamic value co-creation (Gawer and Cusumano 2014; Jones and Tonetti 2020). Competition will move from controlling modular interfaces to shaping learning systems that span organizational boundaries.

Note that these three levels do not operate independently. As Figure 2 illustrates, transformation at each level both emerges from and reinforces changes at adjacent levels (Felin and Foss 2005; Ployhart and Moliterno 2011). Individual-level cognitive transformations shape the development of firm capabilities, which in turn influence ecosystem-level dynamics. Simultaneously, feedback loops operate in reverse. Ecosystem-level structures constrain and enable firm-level strategies, which shape the cognitive tools and frameworks available to individual managers. AI amplifies these cross-level dynamics through three reinforcement mechanisms visible in the figure: refocusing at the individual level (as hybrid cognition continuously updates attention and interpretation) (Raisch and Fomina 2025), reconfiguration at the firm level (as learning-based advantages require ongoing capability renewal) (Teece 2018), and reinforcement at the ecosystem level (as model-centric structures entrench and evolve). Cross-level feedback loops further illustrate how ecosystem dynamics feedback to reshape both firm capabilities and individual cognition, creating a self-reinforcing cycle of AI-driven transformation.

This multilevel synthesis reveals why AI represents more than an incremental technological shift. AI forces a reconceptualization of strategy’s foundational assumptions by simultaneously transforming cognition, capabilities, and

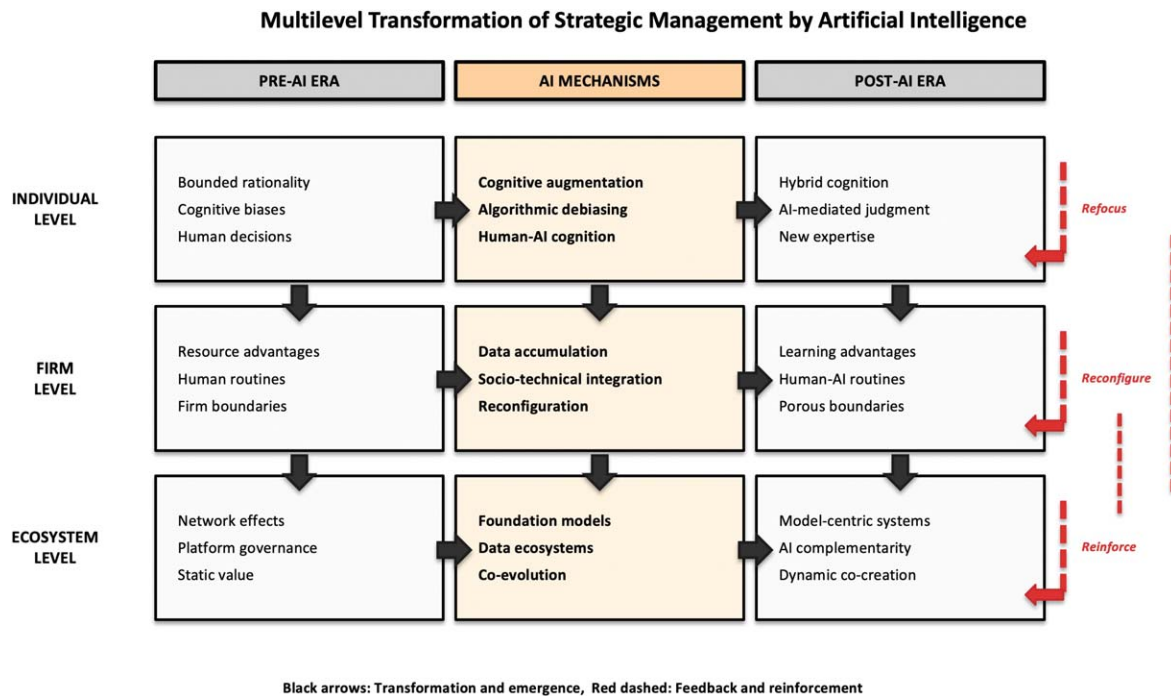


Figure 2: Multilevel transformation of strategic management by AI.

ecosystems, and by creating powerful feedback loops that amplify change across levels (Gavetti 2012; Powell et al. 2011). The traditional separation between internal (firm-level) and external (industry-level) sources of advantage will become increasingly untenable when learning processes, data flows, and algorithmic systems span and connect all three levels (Nambisan et al. 2017). A comprehensive theory of AI-infused strategy must therefore account for this multilevel, interconnected, and dynamically reinforcing architecture of transformation.

5. Conclusion and Empirical Research Agenda

AI is reshaping the foundations of strategic management. It alters what managers perceive, how organizations coordinate, how ecosystems evolve, how value is created and distributed, and how strategic work is performed. Based on this premise, we offer an AI-infused synthesis of strategy theory by (1) reframing classic strategy debates through an AI lens, and (2) extending five major theoretical domains—behavioral strategy, microfoundations, ecosystems, stakeholder RBV, and SAP, to incorporate the distinctive features of the AI landscape. We conclude by synthesizing the paper’s contributions and implications for theory, empirical research, and practice.

In this paper, we have tried to accomplish two interrelated tasks. We have tried to reframe the classic debate in strategic management by viewing it through an AI lens and also offered contemporary extensions to five contemporary theories in strategic research in light of the new AI landscape.

5.1. Reframing Classic Strategy Debates through AI

The longstanding divide between external industry configuration (Porter 1980, 1985) and resource-based explanations (Barney 1991; Wernerfelt 1984) for strategic edge can be reframed through the lens of AI. We note that external industry configuration is increasingly shaped by model-centric ecosystems, data access regimes, and AI governance architectures (Bommasani et al. 2021; Schrepel and Pentland 2025).

Resource-based advantages depend on data richness, fine-tuning pipelines, sociotechnical capabilities, and hybrid learning loops (Agarwal et al. 2022; Raisch and Krakowski 2021). Therefore, AI serves as a synthesizing mechanism, enabling a unified perspective where strategic edge arises from orchestrating learning systems embedded in both the external environment and internal firm capabilities (Iansiti and Lakhani 2020).

5.2. Extending Five Contemporary Strategy Theories

Each contemporary theoretical trend gains depth when integrated with AI. Behavioral Strategy becomes the study of hybrid cognition and human-AI joint decision-making (Powell et al. 2011; Raisch and Fomina 2025). Microfoundations expand to include algorithmic actors, human-AI interaction structures, and sociotechnical emergence (Felin et al. 2015; Murray et al. 2021). Ecosystems theory becomes model-centric, emphasizing data flows, FM cores, and AI-driven complementarities (Jacobides et al. 2018; Xu et al. 2025). Stakeholder RBV foregrounds stakeholder-generated resources (data, feedback), fairness constraints, and ethical governance (Freeman et al. 2021; Floridi et al. 2018). Finally, SAP evolves into AI-augmented strategizing, where agentic tools shape routines, interactions, and legitimacy (Jarzabkowski and Spee 2009; Whittington 2006a). We conclude through our analysis that rather than replacing existing theories, AI extends their explanatory reach.

5.3. Implications for Strategy Research

AI challenges foundational assumptions of strategy theory. Several implications follow:

Strategy must incorporate nonhuman actors as part of microfoundations theory: Microfoundations theory (Felin et al. 2015; Felin and Foss 2005) assumes all strategic actors are human, with firm-level outcomes emerging from individual attributes, interactions, and routines. AI disrupts this by introducing algorithmic agents that exhibit goal-directed behavior, learn from experience, and influence outcomes (Gutiérrez 2024; Kellogg et al. 2020). Future research must theorize how agency is distributed across human-AI ensembles, drawing on actor-network theory (Latour 2005; Callon 1984), distributed cognition frameworks (Riedl et al. 2024; Sidji et al. 2024), and computational organizational theory. The following research questions deserve attention. Under what conditions do algorithmic agents complement versus substitute for human judgment? How do power dynamics shift when AI systems mediate strategic decisions (Shrestha et al. 2019)? What new governance forms emerge when responsibility is distributed between humans and machines (Floridi et al. 2018)?

Cognition becomes distributed between humans and AI, requiring new models of decision-making: Research should examine how AI augmentation affects managerial mental models, decision heuristics, and strategic frames

(Riedl et al. 2024; Gary and Wood 2011). Key questions: How does reliance on AI-generated insights alter cognitive processes underlying strategic choices (Kaplan 2011)? Under what conditions does AI amplify versus mitigate cognitive biases (Kahneman and Klein 2009; Dietvorst et al. 2015)? How do managers calibrate trust in algorithmic versus human judgment (Glikson and Woolley 2020)? Future work should integrate insights from human-computer interaction (Sidji et al. 2024), cognitive science, and behavioral decision theory (Camerer 2003).

Strategic advantage shifts from learning capability to adaptivity: AI fundamentally reorients competitive advantage away from learning capabilities, which were traditionally viewed as the ability to accumulate, codify, and leverage knowledge over time (Teece et al. 1997; Eisenhardt and Martin 2000) toward adaptivity: the capacity to continuously reconfigure in response to real-time feedback. While learning capability emphasizes building knowledge stocks that become durable resources (Grant 1996; Nonaka 1994), adaptivity emphasizes fluid responsiveness where insights immediately trigger reconfigurations rather than being stored for future use (Winter 2003; Zollo and Winter 2002). AI systems enable this shift because they operate through continuous sensing, pattern recognition, and adjustment rather than episodic learning cycles (Faraj et al. 2018). Organizations that excel at accumulating expertise may struggle in AI-infused environments if they cannot translate insights into immediate action. Future research should explore: What organizational structures enable continuous adaptivity rather than periodic learning cycles (Eisenhardt 1989)? How do firms build adaptive capacity without sacrificing the stability required for operational effectiveness (Benner and Tushman 2003)? What governance mechanisms ensure adaptive systems remain aligned with strategic intent? How do culture, leadership, and incentives sustain adaptivity (Samuel et al. 2023) without creating organizational exhaustion or strategic drift (March 1991)?

Ecosystems become model-driven structures rather than purely modular architectures: AI introduces a new organizing logic centered on FMs, data flows, and algorithmic interdependencies (Xu et al. 2025; Bommasani et al. 2021). In AI ecosystems, each participant's interactions generate data that improves a shared FM, creating knowledge spillovers that benefit all members including competitors (Khan et al. 2024; Jones and Tonetti 2020). This shifts competitive advantage from resource ownership to learning speed and ecosystem position (Iansiti and Lakhani 2020). Key questions: How do firms orchestrate multiactor learning systems (Hannah and Eisenhardt 2018)? What governance mechanisms align incentives when value creation depends on shared data and models (Gawer and Cusumano 2014; Jacobides et al. 2019)? Future work should integrate ecosystem theory (Adner and Kapoor 2010; Adner 2017) with research on open innovation (Chesbrough 2003; von Hippel 2005), standards competition (Katz and Shapiro 1985), and collective intelligence (von Krogh et al. 2012).

Stakeholder theory becomes intertwined with data governance and algorithmic fairness: AI makes stakeholders the primary source of critical inputs (data, feedback, content) while exposing them to algorithmic decisions affecting their welfare (Freeman 1984; Freeman et al. 2007). This creates new challenges: How should firms balance value appropriation with fair treatment of stakeholders who provide training data (Zuboff 2019)? What accountability mechanisms ensure AI systems respect stakeholder interests (Diakopoulos 2016)? How do power asymmetries shift when firms control algorithms mediating stakeholder interactions (Plantin et al. 2018)? Research should examine questions of algorithmic justice (Mittelstadt et al. 2016; Barocas and Selbst 2016), data rights (Khatri and Brown 2010), and stakeholder voice in AI governance (Floridi et al. 2018).

SAP must recognize AI as a participant in strategizing: AI transforms strategizing by generating scenarios, recommending actions, automating analyses, and reconfiguring workflows (Jarzabkowski and Spee 2009; Whittington 2006a). Key questions: How does AI change micro-level practices of strategizing (meetings, planning cycles, decision routines) (Jarzabkowski and Kaplan 2015)? What new forms of strategizing emerge when AI enables real-time scenario analysis (Doshi et al. 2025)? How can practitioners navigate tensions between algorithmic recommendations and experiential judgment (Kahneman and Klein 2009)? Future work should employ ethnographic methods, practice theory, and sociomateriality frameworks (Orlikowski 2007; Leonardi 2011; Orlikowski and Scott 2008).

These shifts redefine core constructs such as capability, resource, boundary, rivalry, and coordination (Teece 2018).

5.4. Implications for Methodologies

The integration of AI into strategic management research presents methodological complexities that extend beyond the scope of this conceptual paper. Unlike traditional strategic phenomena where methodological approaches can be relatively standardized, AI-infused strategy research requires context-specific designs that account for multiple interacting factors. The appropriate methodology for studying AI's strategic implications varies systematically based on the theoretical domain under investigation, the nature and role of the AI system itself, the level of risk associated with its deployment, and the organizational and industry context in which it operates. These factors interact in ways that make it impractical to prescribe uniform methodological templates. Instead, researchers must thoughtfully match methods to the specific characteristics of their empirical setting (Bhimani 2020; Christin 2020).

We identify four primary dimensions that should guide methodological choices in AI-infused strategy research, each requiring careful consideration when designing empirical studies. These dimensions can form the foundation for future inquiry into appropriate research designs in this emerging domain:

Strategy domain: The theoretical area under study determines the level of analysis, temporal scale, and appropriate causal inference strategies. For example, behavioral strategy studies examining cognitive effects would benefit from experimental designs that isolate decision-making processes (Powell et al. 2011), while ecosystem research requires network-level data and longitudinal observation of multiactor dynamics (Adner and Kapoor 2010).

Nature of AI engagement: The type of AI system (predictive analytics, generative models, computer vision, robotics, agentic systems) and its organizational role shape data requirements and feasible research designs (Dwivedi et al. 2021). For instance, predictive AI systems with clear outputs enable large quantitative studies and natural experiments, whereas agentic multiagent systems with emergent behaviors require simulation modeling, fine-grained process level data, and intensive case analyses (Klinger et al. 2020).

Level of risk: The potential for harm shapes ethical constraints on research design, ranging from permissible experimentation to observation-only approaches (Floridi et al. 2018). Consider that low-risk consumer applications allow field experiments and A/B testing, while human-critical systems (e.g., healthcare diagnosis, autonomous vehicles) require quasi-experimental designs and participatory methods that prioritize stakeholder safety, and infrastructure-critical systems (energy grids, financial networks) necessitate simulation-based approaches where live experimentation is not feasible.

Organizational and industry context: Organizational characteristics (size, structure, culture) and industry dynamics (competitive intensity, regulatory regime, stakeholder power) affect data accessibility, identification strategies, and generalizability (Bloom et al. 2019). Large established firms provide archival data suitable for multilevel quantitative analysis, while startups require intensive case approaches. On the other hand, heavily regulated industries (healthcare, finance) demand close collaboration with oversight bodies and emphasize observational designs, whereas fast-moving technology sectors create natural experiments through continuous AI deployment (Cockburn et al. 2018).

These four dimensions interact to create a complex methodological landscape. A comprehensive treatment of how researchers should navigate these trade-offs, including guidance on matching specific research designs to specific configurations of domain, AI type, risk level, and context, represents a substantial undertaking that merits dedicated development in future work. Our aim in this paper has been to establish the theoretical foundations for understanding how AI transforms strategy. Translating these theoretical insights into rigorous empirical research requires equally careful methodological development.

5.5. Implications for Managerial Practice

Building hybrid cognitive capabilities: Managers must develop competencies for leading organizations where cognition is distributed between humans and AI (Raisch and Fomina 2025; Jarrahi 2018), which include cultivating algorithmic literacy, fostering cultures balancing data-driven insights with experiential judgment (Samuel et al. 2023), designing governance mechanisms to clarify when humans should defer to or override algorithms (Glikson and Woolley 2020), and investing in training for effective human-AI collaboration. Leaders must model constructive collaboration and create norms to legitimize both algorithmic inputs and human intuition (Shrestha et al. 2019).

Orchestrating AI-enabled learning: Competitive advantage increasingly depends on learning velocity - the ability to rapidly improve systems through data and experimentation (Iansiti and Lakhani 2020; Agarwal et al. 2022). This requires mechanisms for continuous data collection and model retraining, organizational structures enabling rapid experimentation (Eisenhardt 1989), metrics tracking learning progress and algorithmic performance, and cultures rewarding learning from successes and failures (March 1991; Samuel et al. 2023). Managers must also navigate tensions between protecting proprietary data and participating in open ecosystems accelerating collective learning (Chesbrough 2003; Laursen and Salter 2006).

Designing governance mechanisms: AI ecosystems require new governance approaches addressing data sharing, intellectual property, quality standards, value allocation, and conflict resolution (Gawer and Cusumano 2014; Constantinides et al. 2018). Managers should proactively design governance mechanisms rather than allowing de facto arrangements to emerge organically (Boudreau 2010).

Navigating ethical dilemmas: AI adoption confronts managers with pressing questions. How can we address algorithmic bias and ensure fairness (Barocas and Selbst 2016; Mehrabi et al. 2021)? What transparency should we provide to different stakeholders (Diakopoulos 2016; Samuel 2024)? How do we manage job displacement and workforce transitions (Bessen et al. 2025; Brynjolfsson and McAfee 2014)? Where should we set boundaries around surveillance and privacy (Zuboff 2019)? What is our responsibility for our impacts on society (Floridi et al.

2018)? Managers must decide whether to establish ethics committees, conduct impact assessments, invest in bias detection, develop explainability practices, and support workforce reskilling. They must consider a fundamental question: Is our role simply to comply with regulations, or should we proactively shape AI development in socially responsible directions?

Anticipating competitive shifts: AI may fundamentally alter competitive dynamics (Christensen et al. 2015; Iansiti and Lakhani 2020). Managers must determine the answers to the following questions. How will AI reshape customer preferences and switching behaviors? Will AI lower entry barriers for new competitors (Bresnahan and Greenstein 1999)? Will AI commoditize our capabilities (Brynjolfsson and McAfee 2014)? How will AI affect economies of scale, scope, and firm boundaries (Williamson 1985)? Under different scenarios, how might industry structure evolve? What early warning signals should we monitor to anticipate rather than react to disruption (Christensen 1997)?

Building organizational resilience: AI introduces new uncertainties demanding resilience. Managers must decide. How much slack should we maintain for experimentation and failure recovery (March 1991)? How can we balance risky AI investments with stable core businesses (Benner and Tushman 2003)? What rapid response capabilities do we need for algorithmic failures? How can we foster cultures treating failure as learning (Levinthal and March 1993)?

Ultimately, AI strategy should be integrated into core strategic planning, not siloed within IT departments (Ransbotham et al. 2017). Managers who successfully navigate these challenges will position their organizations to thrive in an AI-infused competitive landscape. Those who treat AI as merely another technology risk strategic obsolescence.

5.6. Final Synthesis

AI challenges strategic management to rethink its foundational assumptions. Just as industrial organization economics, resource-centric perspectives, and behavioral theories transformed strategy over prior decades, AI represents the next major theoretical frontier. It introduces new actors (algorithmic agents), new resources (data and models), new forms of competition (learning races), and new organizing logics (interconnected network orchestration).

By analyzing five influential strategy theories, articulating a comprehensive theory of agentic AI, and proposing a wide-ranging empirical agenda, this paper seeks to provide a foundation for the next generation of strategy research. The field now has an opportunity to integrate insights from behavioral science, computer science, organizational theory, and ethics to build richer explanations of strategic edge in an AI-infused world.

The central message of this paper is clear: AI does not merely necessitate changes to the practice of strategy; it compels changes to the theory of strategy. The challenge ahead is to empirically test, refine, and extend the ideas outlined here so that the discipline can continue to offer rigorous, relevant insights in an era where intelligence, human and artificial, is at the core of strategic competition.

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