



Artificial Intelligence and Strategic Management: A Theoretical Analysis of Technological Innovation, Competitive Advantage, and Sustained Organizational Performance in Businesses

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Abstract

Strategic management theory has absorbed successive technological disruptions by asking a consistent question: does the new technology change the sources from which firms derive sustained competitive advantage, or does it merely change the speed at which firms pursue advantages the field already understands? This paper argues that artificial intelligence (AI) demands a more differentiated answer than either alternative offers on its own. Integrating the resource-based view, dynamic capabilities theory, and behavioral strategy with recent empirical evidence on AI adoption, innovation, and firm performance, the paper develops a theoretical account in which AI's strategic significance operates through three related but analytically distinct pathways: a technological-innovation pathway, in which AI functions alternately as an originator and a facilitator of novel solutions; a competitive-advantage pathway, in which AI capability, rather than AI technology as such, determines whether adoption yields defensible advantage; and a sustainable-performance pathway, in which AI's contribution to environmental, social, and governance outcomes is increasingly documented but remains mechanistically underexplained. The paper shows that these three pathways share a common vulnerability the applied strategy literature has not adequately addressed: none converts automatically into durable organizational performance without a governance layer capable of allocating decision authority appropriately between algorithmic recommendation and human strategic judgment. Drawing on evidence that superior algorithmic predictions frequently fail to improve real decisions once human override authority is exercised without adequate calibration, the paper proposes an integrated model linking AI capability, the exploration-exploitation balance, and sustainable performance, and considers the implications of that model for strategic management practice, policy, and future research.

Keywords: artificial intelligence; strategic management; technological innovation; competitive advantage; dynamic capabilities; resource-based view; sustainable performance; ESG.

Introduction

Every major wave of technological change in business history has forced strategic management theory to revisit its central question: where does sustained competitive advantage actually come from, and does the new technology change the answer. Porter's (1985) foundational account locates advantage in a firm's position within its industry structure and the activities through which it creates value more efficiently or more distinctively than rivals; Barney's (1991) resource-based view relocates the source of advantage inside the firm, in resources that are valuable, rare,



inimitable, and non-substitutable; and Teece, Pisano, and Shuen's (1997) dynamic capabilities perspective relocates it again, in the firm's capacity to sense opportunities, seize them, and reconfigure its resource base as conditions change. Artificial intelligence (AI) arrives into this theoretical lineage carrying a specific and, this paper argues, still unresolved question: does AI represent a resource in Barney's sense, a capability in Teece et al.'s sense, or something that does not map cleanly onto either category because of how easily it can be acquired, replicated, and redeployed across firms and industries simultaneously.

The empirical literature responding to this question has grown rapidly but remains fragmented across outcome variables that are rarely examined together. One stream documents AI's contribution to innovation specifically, with Haefner, Wincent, Parida, and Gassmann (2021) proposing that AI functions as both an originator and a facilitator of novel solutions, and Cockburn, Henderson, and Stern (2019) proposing, at an economy-wide level, that AI functions as a general-purpose "method of invention" whose significance lies less in any single application than in its capacity to reorganize how firms conduct research and development across sectors. A second stream examines AI's contribution to firm performance and competitive advantage more directly, with Mikalef and Gupta (2021) finding that it is AI capability — the organizational combination of technology, human skill, and intangible assets — rather than AI technology alone that predicts organizational creativity and performance, and Krakowski, Luger, and Raisch (2023) finding, through a controlled study of competitive chess, that AI adoption simultaneously destroys some traditional sources of human advantage and creates new ones rooted in the specific skill of human–AI interaction. A third, more recent stream examines AI's contribution to sustainable and ESG-oriented performance specifically, with Song, Mi, Bian, Tu, and He (2025) finding, using a large panel of Chinese listed firms, that AI adoption policy significantly improves corporate ESG performance, particularly for firms starting from a weaker digital and sustainability base.

Each of these three streams offers credible evidence, but the theoretical relationship between them — whether innovation, competitive advantage, and sustainable performance represent the same underlying strategic mechanism applied to different outcome measures, or genuinely distinct pathways with different antecedents, different boundary conditions, and different failure modes — has received considerably less sustained attention than any one outcome examined in isolation. This paper addresses that gap. Its central argument is that **AI's strategic significance runs through three analytically distinct pathways — technological innovation, competitive advantage, and sustainable performance — that share a common structural vulnerability: none of the three converts automatically into durable organizational outcomes without a governance layer that correctly allocates decision authority between algorithmic recommendation and human strategic judgment.** Where that governance layer is absent or poorly calibrated, the evidence reviewed in this paper suggests firms can simultaneously exhibit improved AI capability on conventional metrics and see no corresponding improvement, or even a deterioration, in the strategic decisions that capability is meant to inform. The paper develops this argument by reviewing the relevant theoretical foundations; examining the evidence on AI's contribution to innovation, competitive advantage, and sustainable performance in turn; and proposing an integrated model connecting the three pathways through the governance condition this paper identifies as their common requirements.

**Conceptualizing AI as a Strategic Resource**

Von Krogh (2018) offers a useful starting point for conceptualizing AI's strategic role, proposing that AI systems relevant to organizations can be understood through the interaction of task inputs (data), task processes (algorithms), and task outputs (decisions or recommendations) — a framing that treats AI not as a discrete tool but as a genuinely organizational phenomenon whose strategic significance depends on how these three elements interact with existing firm resources and routines. Duan, Edwards, and Dwivedi (2019), tracing the evolution of AI research relevant to organizational decision-making, distinguish the current generation of AI systems from earlier expert systems by their capacity to learn from data rather than operate from fixed rule sets — a distinction with direct strategic consequence, since it means AI's contribution to a firm's resource base is not fixed at the point of acquisition but continues to evolve, for better or worse, with the data the organization generates and the decisions it makes using that data.

This paper treats AI's strategic role as operating simultaneously at three levels that strategic management theory has historically treated somewhat separately: the resource level, where AI functions as an input a firm can acquire, of the kind Barney's (1991) resource-based view evaluates against criteria of value, rarity, inimitability, and non-substitutability; the capability level, where AI functions as part of a broader organizational process for sensing, seizing, and reconfiguring resources, of the kind Teece et al.'s (1997) and Eisenhardt and Martin's (2000) dynamic capabilities perspectives evaluate; and the governance level, where AI functions as an input to specific strategic decisions whose quality depends on how authority is allocated between algorithmic output and human judgment. The central claim this paper develops is that strategic management research has made considerable progress on the first two levels while leaving the third comparatively under examined, and that this gap is precisely where the applied literature's optimism about AI's strategic value most often outruns evidence.

Theoretical Foundations

that sustained competitive advantage requires resources that are valuable, rare, inimitable, and non-substitutable — a standard that a purchased or licensed AI technology, available to competitors on broadly similar commercial terms, does not automatically meet. This is a genuine theoretical problem for any strategic account of AI that stops at the level of technology acquisition: if two competing firms can license comparable AI systems from the same handful of technology vendors, the resource-based view predicts no sustained advantage should follow from that acquisition alone, however much the technology improves either firm's operations in absolute terms. Mikalef and Gupta (2021) resolve this problem empirically by distinguishing AI technology from AI capability — the organizational combination of tangible resources, human skills, and intangible assets required to deploy that technology effectively — and finding that it is capability, not technology, that predicts organizational creativity and firm performance. This distinction does substantial theoretical work throughout this paper: it explains why firms with access to nominally identical AI tools frequently realize very different strategic outcomes, and it establishes AI capability, rather than AI technology, as the object of analysis strategic management theory actually needs.



Dynamic Capabilities: Sensing, Seizing, and Reconfiguring in an AI Context

Where the resource-based view explains why AI technology alone is an insufficient basis for advantage, dynamic capabilities theory explains how firms convert that technology into advantage over time. Teece et al. (1997) characterize dynamic capabilities as a firm's capacity to sense opportunities and threats, seize opportunities through timely resource allocation, and reconfigure its resource base as its environment changes — a three-part structure this paper argues maps onto AI's strategic contribution unusually well. AI's contribution to sensing is well documented in the analytics and prediction literature; its contribution to seizing is documented in evidence on AI-accelerated decision-making and resource allocation; its contribution to reconfiguring is documented in evidence on AI-enabled organizational learning and adaptation. Eisenhardt and Martin (2000), extending Teece et al.'s framework, add an important qualification directly relevant to AI specifically: they argue dynamic capabilities are best understood as specific, identifiable organizational processes — product development routines, strategic decision-making processes, alliancing capabilities — that exhibit meaningful commonality across firms, which implies they are more imitable than the resource-based view's classical emphasis on inimitability would suggest, particularly in moderately dynamic markets where dynamic capabilities come to resemble standardized best practice rather than idiosyncratic, firm-specific routines. Applied to AI, this qualification suggests that AI-enabled dynamic capabilities may erode as a source of sustained advantage more quickly than the resource-based view's classical criteria would predict, precisely because AI-enabled sensing and seizing routines are unusually well suited to codification and diffusion across firms.

Bounded Rationality and the Behavioral Foundations of AI-Enabled Strategy

Simon's (1955) concept of bounded rationality supplies this paper's third theoretical foundation, specifying precisely what AI intervenes in at the level of strategic decision-making: the cognitive and informational limits that prevent strategists from evaluating every available alternative before deciding. Cyert and March's (1963) behavioral theory of the firm extends this individual-level constraint to the organizational level, arguing that firms satisfice across competing internal objectives and search for solutions only in the local neighborhood of existing practice. Applied to strategic management specifically, this behavioral tradition supplies an important corrective to purely resource-based and dynamic-capabilities accounts of AI's strategic value: it suggests that AI's contribution is not simply to supply better resources or better organizational processes in the abstract, but to relax the specific cognitive constraints that have historically limited how broadly and how rigorously strategists search for alternatives before committing an organization's resources to a particular course of action. Whether AI-enabled search actually expands the strategic alternatives a firm considers, or merely accelerates evaluation within the same narrow local neighborhood Cyert and March describe, is an empirical question this paper argues has not been adequately separated in the applied literature.

The Automation–Augmentation Paradox in Strategic Management

Raisch and Krakowski (2021) provide this paper's fourth theoretical foundation, arguing that AI applications in management divide into automation, where AI takes over a task previously performed by a human, and augmentation, where humans and AI collaborate to perform a task



neither could perform as well alone — and, critically, that these are not independent choices a firm can make separately but interdependent tensions that coexist within the same organizational system. Applied to strategic management specifically, this paradox has a direct implication this paper treats as central: a firm that emphasizes AI automation in operational decision-making, at the expense of the organizational structures that support augmented strategic judgment, may find its capacity for genuinely strategic, non-routine decision-making eroding even as its operational efficiency improves. Jarrahi (2018) develops a complementary argument through the lens of human–AI symbiosis, proposing that AI is best suited to fast, data-intensive, and analytical aspects of decision-making, while humans retain comparative advantage in the intuitive, holistic, and socially embedded aspects — a division of labor with direct relevance to strategic management, where decisions frequently combine both types of demand simultaneously.

Absorptive Capacity and the Limits of AI-Enabled Learning

A fifth theoretical foundation, developed well before AI existed in its current form but directly relevant to how firms actually convert AI-generated information into strategic value, comes from Cohen and Levinthal's (1990) concept of absorptive capacity — a firm's ability to recognize the value of new external information, assimilate it, and apply it to commercial ends. Cohen and Levinthal argue that absorptive capacity is largely a function of a firm's prior related knowledge, meaning organizations with stronger existing knowledge bases are better positioned to recognize and exploit valuable new information, including information generated by new technology, than organizations without that prior foundation. This concept has direct and, this paper argues, underappreciated relevance to AI-enabled strategy: an AI system may generate genuinely valuable strategic insight, but a firm's capacity to recognize that insight as valuable, to assimilate it into existing strategic frameworks, and to act on it commercially depends on organizational knowledge that exists prior to, and independent of, the AI system itself. This reframes the resource-based and dynamic-capabilities accounts developed above in an important way: AI capability, in Mikalef and Gupta's (2021) sense, is not simply a matter of combining technology with human skill in the abstract, but a matter of combining technology with the specific, cumulative prior knowledge that determines whether a given organization can actually absorb what the technology produces. This absorptive-capacity lens also supplies a theoretical explanation for the catching-up pattern examined later in this paper's discussion of sustainable performance: firms with weaker prior digital and sustainability knowledge might be expected, on Cohen and Levinthal's logic, to absorb AI-generated sustainability insight less effectively than firms with stronger prior foundations, a prediction that stands in some tension with the empirical catching-up pattern this paper reviews, and which this paper flags as a genuine theoretical puzzle rather than resolving conclusively.

AI and Technological Innovation

AI as Originator and Facilitator of Innovation

Haefner et al. (2021) propose that AI plays two distinct roles in innovation management: as an originator, generating novel combinations or solutions a human team would not have identified, and as a facilitator, supporting and accelerating human-led innovation processes without replacing the human role in judgement and selection. This originator-facilitator distinction has direct strategic



significance because the two roles carry different implications for competitive advantage: origination, if it produces genuinely novel and valuable combinations, has the potential to meet Barney's (1991) rarity criterion directly, while facilitation primarily improves the efficiency of an innovation process whose ultimate outputs remain determined by human strategic judgment, and therefore contributes to advantage only indirectly, through whatever advantage that judgment itself commands. Cockburn, Henderson, and Stern (2019) extend this picture to the level of the broader innovation system, proposing that AI's most consequential contribution to innovation may not be any single originating or facilitating application, but AI's function as a general-purpose "method of invention" that reorganizes the process of research and development itself across essentially every sector to which it diffuses. Examining shifts in AI-related publication and patenting activity, they find evidence consistent with deep learning functioning as this kind of general-purpose invention technology, with research activity substituting away from routinized, labor-intensive investigation toward research that exploits the interplay between large datasets and increasingly capable prediction algorithms. For strategic management specifically, this general-purpose-technology framing implies that firms competing primarily on the originator or facilitator dimensions of AI-enabled innovation, considered in isolation, may be competing on a narrower and more transient basis than firms that restructure their broader innovation processes around AI's general-purpose capabilities — a distinction the applied strategy literature has not yet adequately drawn.

Exploration and Exploitation in an AI Organization

March's (1991) foundational distinction between exploration — the pursuit of new knowledge, novel alternatives, and organizational variation — and exploitation — the refinement and efficient use of existing knowledge and routines — offers a theoretical lens through which AI's innovation contribution can be evaluated more precisely than the originator-facilitator distinction alone allows. March's central insight, that organizations face a persistent trade-off between exploration and exploitation because resources devoted to one are generally unavailable for the other, raises a specific question for AI-enabled strategy this paper argues deserves more attention than it has received: does AI relax this trade-off, by making both exploration and exploitation simultaneously cheaper and faster, or does it merely shift the trade-off's location, by making exploitation so efficient that organizations under-invest in exploration relative to what March's framework suggests long-run adaptability requires.

The evidence reviewed in the preceding subsection offers a tentative, though not yet definitive, answer to this question. Haefner et al.'s (2021) facilitator role for AI maps closely onto exploitation — accelerating and refining existing innovation processes — while the originator role maps more ambiguously onto exploration, since AI-generated novel combinations still draw on historical data and existing patterns rather than genuinely unprecedented variation in March's original sense. Cohen and Levinthal's (1990) absorptive-capacity concept adds a further complication this paper treats as significant: even where AI genuinely originates novel combinations that would qualify as exploration in March's sense, a firm's capacity to recognize and act on that novelty depends on prior organizational knowledge the AI system itself does not supply, meaning firms with weaker absorptive capacity may fail to convert AI-enabled exploration into genuine strategic variation regardless of how novel the AI's output actually is. This paper's reading of the combined evidence



is that AI's demonstrated strength currently lies disproportionately on the exploitation side of March's distinction, which raises a genuine strategic risk this paper treats as an important, underexamined implication: organizations that adopt AI primarily to accelerate exploitation, without a deliberate, offsetting investment in the kind of genuinely novel exploration March's framework identifies as necessary for long-run adaptability, and without the absorptive capacity Cohen and Levinthal identify as necessary to recognize valuable novelty when AI does produce it, may be trading short-run efficiency gains for exactly the kind of organizational rigidity March's original analysis warned against.

AI and Competitive Advantage

From AI Technology to AI Capability: The Substitution–Complementation Dynamic

Krakowski, Luger, and Raisch (2023) provide this paper's most direct empirical evidence on how AI adoption actually reshapes competitive advantage over time, using competitive chess as a controlled setting in which to observe the same players' relative performance across conventional, human-assisted, and fully algorithmic tournament formats. They find that AI adoption triggers substitution and complementation dynamics operating simultaneously rather than as alternatives: players' traditional competitive capabilities become obsolete even as new, persistent sources of advantage emerge specifically from the way particular humans interact with AI systems. This finding does substantial theoretical work for the present paper because it demonstrates, empirically rather than by assertion, that AI capability in Mikalef and Gupta's (2021) sense is not a generic organizational attribute firms either possess or lack, but something closer to a skill in human–machine interaction that develops unevenly across individuals and organizations — precisely the kind of resource Barney's (1991) rarity and inimitability criteria would predict is more durable as a source of advantage than the underlying AI technology itself.

Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug, and Tchatchouang Wanko (2020), analyzing AI-based transformation projects across a range of industrial sectors, document AI's association with firm performance through several intermediating business processes — improved customer experience, more adaptive responses to changing market conditions, new business-model creation, and better-optimized supply and demand forecasting — rather than through any single direct effect. This pattern of intermediation is consistent with the dynamic-capabilities interpretation this paper has developed: AI's contribution to performance runs primarily through the organization's capacity to sense changing conditions and reconfigure its processes in response, rather than through a static efficiency gain that would eventually be competed away as rival firms adopt comparable technology. Benbya, Davenport, and Pachidi (2020), reviewing the state of AI in organizations more broadly, reach a related conclusion: firms that treat AI implementation as an ongoing organizational learning process, rather than a discrete technology deployment, are considerably more likely to realize sustained performance benefits than those that treat AI adoption as a one-time capital investment — a finding this paper reads as direct support for the capability-over-technology distinction this section has developed.

Decision Authority and the Limits of Algorithmic Advantage



The evidence reviewed so far might suggest that firms simply need to invest in AI capability, rather than AI technology alone, to secure durable competitive advantage. Kim, Glaeser, Hillis, Kominers, and Luca (2024) complicate this conclusion directly. Evaluating a pilot comparing algorithms of differing sophistication in a municipal inspections context, they find both algorithms delivered substantial, measurable prediction gains over the existing prioritization method — yet these prediction gains did not translate into improved decisions, because officials retaining override authority exercised it frequently, often citing considerations the algorithm had not been designed to capture, and the resulting decisions were, on average, no better than those made without algorithmic assistance. Applied to strategic management, this finding carries a specific and consequential implication: a firm can build genuine AI capability, in Mikalef and Gupta's (2021) sense, and still see no corresponding improvement in the strategic decisions that capability is meant to inform, if the executives and managers positioned to act on AI-generated strategic recommendations are inclined to override them in ways unconnected to genuine additional information they possess. Kellogg, Valentine, and Christin (2020), examining algorithmic control more broadly across occupational contexts, add a further dimension to this concern, finding that AI-based systems function simultaneously as tools that augment decision-making and as mechanisms through which organizations exercise control over the humans whose decisions those systems inform — a duality this paper argues complicates any simple account of AI capability converting smoothly into competitive advantage.

Industry Structure and Positioning in the AI Era

Porter's (1985) classical framework locates competitive advantage in a firm's position within its industry's structure and the activities through which it creates value distinctively. AI's effect on this positioning logic operates at two levels this paper distinguishes explicitly. At the industry level, AI can alter the structural forces Porter's framework identifies — lowering barriers to entry in data-intensive industries where AI substitutes for capital or experience that previously constituted a barrier, or raising them in industries where AI capability itself requires scale and proprietary data difficult for new entrants to replicate. At the firm level, AI can alter the specific activities through which a firm differentiates itself or achieves cost leadership, but the evidence reviewed throughout this section suggests this activity-level effect is considerably more contingent on organizational capability and governance than a purely positional account would predict. This paper's reading is that Porter's positioning logic remains relevant to AI-era strategy, but that AI's effect on industry structure is itself firm-capability-dependent in a way that creates a genuine interpretive circularity: a firm's AI capability shapes how AI reshapes the industry structure that firm competes within, which in turn shapes what AI capability is worth possessing — a dynamic that the largely static, cross-sectional evidence reviewed in this paper cannot yet fully resolve.

This circularity has a further implication worth making explicit. Classical industry-structure analysis treats the five forces — rivalry, entry threat, supplier power, buyer power, and substitute threat — as largely exogenous conditions a firm positions itself against; AI complicates this exogeneity assumption specifically because firms with stronger AI capability are increasingly able to actively reshape the forces themselves, rather than simply respond to them. A firm with superior AI-enabled customer analytics, for instance, may not merely position itself favorably against



existing buyer power but actively increase switching costs and reduce buyer power directly, converting what Porter's framework treats as an environmental given into an outcome the firm's own capability investment partially determines. This paper reads this shift as consistent with, rather than contradictory to, the dynamic-capabilities perspective developed earlier: it is precisely the kind of environmental reconfiguration Teece et al.'s (1997) sensing-seizing-reconfiguring logic anticipates, applied now to the industry structure itself rather than only to the firm's internal resource base. The strategic implication is that firms evaluating AI investment purely in positional terms — where do we sit relative to existing industry structure — may be under-valuing AI's capacity to shift that structure in the investing firm's favor, provided the capability and governance conditions this paper has identified are both present.

AI and Sustainable Organizational Performance

Durable Performance: Beyond a Static Efficiency Gain

This paper uses “sustainable organizational performance” in two related but distinct senses that the strategic management literature has not always carefully separated: performance that is durable over time, in the sense the resource-based view and dynamic capabilities theory address directly, and performance that is sustainable in the environmental, social, and governance sense increasingly central to contemporary strategic management practice. The evidence reviewed in the preceding section speaks primarily to the first sense, establishing that AI's contribution to durable advantage depends on capability and governance rather than technology alone. The second sense requires separate theoretical attention, since a firm could plausibly achieve durable financial advantage from AI adoption while its AI-related environmental footprint, labor practices, or governance transparency deteriorate — a genuine tension this paper argues the two senses of sustainability need to be examined together rather than treated as automatically aligned.

The AI–ESG Nexus: Evidence and Mechanisms

Song, Mi, Bian, Tu, and He (2025), exploiting China's national AI Innovation and Development Pilot Zone policy as a quasi-natural experiment across a large panel of listed firms, find that AI-policy exposure significantly and robustly improves corporate ESG performance, with effects operating through three identified mechanisms: AI-driven digital transformation, green innovation, and strengthened corporate social responsibility disclosure. Critically for this paper's argument, they find this ESG-improving effect is strongest precisely among firms and regions with initially weaker digital and sustainability foundations — a “catching-up” pattern consistent with technological catch-up theory, in which technological followers achieve disproportionate gains from adopting an already-proven technology relative to leaders who have less remaining gap to close. This finding has a direct implication for the durability question raised above: if AI's ESG-improving effect is strongest among catching-up firms, the competitive-advantage implications of AI-enabled ESG improvement may be temporary at the industry level even where they are substantial at the individual-firm level, since the mechanism generating the improvement is convergence toward an existing frontier rather than the creation of a new one.

The mechanisms Song et al. (2025) identify connect directly to this paper's dynamic-capabilities framing. Digital transformation and green innovation both function as dynamic-



capability-building processes in Teece et al.'s (1997) sense — sensing environmental and regulatory change, seizing opportunities for resource reconfiguration around sustainability objectives, and reconfiguring organizational routines accordingly — while strengthened CSR disclosure functions more directly as an information-and-legitimacy mechanism connecting internal capability-building to external stakeholder perception. This paper reads the evidence as suggesting that AI's sustainable-performance pathway is not theoretically distinct from its competitive-advantage pathway so much as a specific application of the same dynamic-capabilities logic to sustainability-relevant sensing, seizing, and reconfiguring — which implies the same governance vulnerability this paper has identified throughout should apply here as well, though the ESG-specific evidence available to date has not directly tested this implication.

The Twin Transition: Digital and Green Strategy Integration

A further theoretical consideration concerns the increasingly influential twin-transition literature, which argues that digital and green organizational transformation are mutually reinforcing rather than independent strategic tracks. Song et al.'s (2025) finding that AI-driven digital transformation and green innovation operate as parallel, partially overlapping mechanisms driving ESG improvement offers empirical support for this twin-transition logic specifically in the AI context. For strategic management theory, the practical implication is that firms treating AI investment and sustainability investment as separate strategic initiatives, evaluated against separate performance metrics and governed by separate organizational functions, may be forgoing the synergy the twin-transition and dynamic-capabilities literatures both suggest is available when the two are integrated — a coordination requirement this paper argues belongs alongside the decision-authority governance requirement identified earlier as a condition for AI's strategic value to be fully realized.

Toward an Integrated Theoretical Model

Bringing the preceding sections together, this paper proposes an integrated model in which AI's contribution to sustainable organizational performance runs through three parallel pathways — technological innovation, competitive advantage, and ESG-oriented sustainability — each grounded in the dynamic-capabilities logic of sensing, seizing, and reconfiguring, and each conditioned on the same underlying requirement: an organizational governance layer capable of allocating decision authority appropriately between algorithmic recommendation and human strategic judgment. Figure 1 summarizes this model. AI capability, built from the combination of technology, human skill, and organizational routine that Mikalef and Gupta (2021) and Krakowski et al. (2023) identify, feeds into exploration-oriented innovation activity and exploitation-oriented efficiency activity simultaneously, in the sense March (1991) distinguishes; these feed in turn into competitive-advantage and sustainable-performance outcomes; and the entire structure is conditioned by a governance layer addressing decision authority, without which the evidence reviewed throughout this paper suggests the preceding stages can advance considerably while final organizational outcomes remain unchanged or even deteriorate.

Implications for Strategic Management Practice



For executives evaluating AI investment, the model developed here suggests the central strategic question is not simply how much to invest in AI technology, but whether the organization is simultaneously building the capability layer Mikalef and Gupta (2021) and Krakowski et al. (2023) identify as necessary for that technology to translate into advantage, and the governance layer this paper has identified as necessary for that capability to translate into improved decisions. An organization that invests heavily in AI technology while neglecting either layer should expect, on the evidence reviewed in this paper, considerably weaker returns than the technology's raw capability would predict.

For the exploration-exploitation balance specifically, March's (1991) framework suggests firms should track AI's effect on this balance explicitly rather than assuming AI-enabled efficiency gains are strategically neutral. Given this paper's reading that AI's current demonstrated strength lies disproportionately on the exploitation side, firms may need to make a deliberate, offsetting investment in AI-enabled or AI-complementary exploration — genuinely novel experimentation, rather than accelerated refinement of existing approaches — to avoid the long-run adaptability costs March's original analysis identifies as the risk of exploitation-dominant organizational learning.

For sustainability strategy specifically, Song et al.'s (2025) catching-up finding suggests firms starting from a weaker digital or ESG base may find AI adoption disproportionately valuable for closing competitive gaps, but should not expect this catching-up advantage to persist once the gap closes; sustained ESG-related advantage, on this paper's reading, will depend on the same capability-and-governance conditions this paper has identified for competitive advantage more generally, not on AI adoption considered as an ESG intervention in isolation. Firms are accordingly best served by integrating AI and sustainability strategy within a single governance structure, consistent with the twin-transition logic this paper has reviewed, rather than managing the two as parallel but organizationally separate initiatives.

Finally, the industry-structure discussion above suggests a further practical implication for how firms conduct competitive analysis under AI-era conditions: strategists should treat AI capability as a variable competitors can use to actively reshape industry forces, not merely as an efficiency lever operating within a fixed structure. Practically, this means competitive intelligence functions should track not only competitors' AI adoption levels but the specific mechanisms — customer-switching-cost manipulation, supplier-relationship restructuring, entry-barrier construction — through which that adoption is being used to reshape the industry environment itself, since the evidence and theory reviewed in this paper both suggest this reshaping capacity, rather than AI-enabled efficiency alone, may be where the most durable strategic returns to AI investment ultimately reside.

Directions for Future Research

Several gaps follow from the theoretical model developed above. First, the three pathways this paper distinguishes analytically — innovation, competitive advantage, and sustainable performance — have rarely been tested as parallel, interacting processes within the same empirical study; research designs capable of tracking all three simultaneously within the same organizations



would test whether the shared governance dependency this paper proposes actually produces the cross-pathway correlation the model predicts.

Second, the exploration-exploitation question this paper raises — whether AI relaxes March's (1991) trade-off or merely relocates it toward exploitation — has not been directly tested; longitudinal research tracking the composition of firms' innovation activity before and after significant AI adoption, using established exploration-exploitation measures, would give this paper's tentative reading an empirical foundation it currently lacks.

Third, Krakowski et al.'s (2023) chess-based methodology for isolating substitution and complementation dynamics offers a promising template that has not yet been applied to sustainability-relevant strategic decisions specifically; adapting a comparable controlled design to ESG-relevant decision tasks would test whether the same substitution-complementation pattern this paper has extended theoretically to the sustainability pathway actually holds empirically.

Finally, the governance layer this paper identifies as common to all three pathways has been developed conceptually rather than measured directly; research operationalizing decision-authority governance as a distinct organizational construct — perhaps through documented-override rates or explicit authority-allocation policies, of the kind Kim et al.'s (2024) evidence suggests — would allow the central claim of this paper's integrated model to be tested with the same empirical rigor the innovation and competitive-advantage literatures have already achieved for their respective pathways.

A fifth gap concerns the tension this paper has flagged but not resolved between Cohen and Levinthal's (1990) absorptive-capacity prediction and Song et al.'s (2025) empirical catching-up finding: absorptive-capacity theory would predict firms with weaker prior knowledge should struggle to exploit AI-generated insight, yet the ESG evidence reviewed in this paper finds exactly these firms benefiting disproportionately from AI-policy exposure. Research examining whether this apparent tension reflects a genuine theoretical boundary condition — perhaps because policy-driven AI adoption supplies a form of externally structured knowledge transfer that substitutes for the internally accumulated prior knowledge Cohen and Levinthal's original framework emphasizes — or an artifact of the specific Chinese policy-driven setting Song et al. examine, would meaningfully advance this paper's theoretical synthesis.

Conclusion

Artificial intelligence's significance for strategic management theory lies not in any single capability it adds to organizations, but in the way it simultaneously touches the resource base classical strategy theory examines, the dynamic capabilities that convert resources into advantage, and the behavioral and governance conditions under which strategic decisions are actually made. This paper has argued that AI's strategic effects are best understood as running through three parallel pathways — technological innovation, competitive advantage, and sustainable organizational performance — each grounded in the same underlying logic of sensing, seizing, and reconfiguring that dynamic capabilities theory identifies, and each dependent on a governance layer that existing strategic management frameworks have not adequately theorized. The evidence reviewed throughout this paper, from Mikalef and Gupta's (2021) capability-technology distinction to Kim et



al.'s (2024) demonstration that superior algorithmic predictions can leave organizational decisions unimproved, points toward a conclusion the applied AI-and-strategy literature has generally understated: the technical sophistication of a firm's AI resources is a comparatively poor predictor of its ultimate strategic outcomes, relative to the organizational capability and governance conditions that determine whether those resources are actually converted into durable advantage.

This conclusion should not be read as diminishing the genuine theoretical progress the literature reviewed in this paper represents. Barney (1991), Teece et al. (1997), Porter (1985), and March (1991) each supplied strategic management with durable analytical tools decades before AI existed in its current form, and the central achievement of the more recent literature this paper has reviewed — Mikalef and Gupta (2021), Krakowski et al. (2023), Kim et al. (2024), Song et al. (2025) — has been to show, empirically, exactly where those durable tools continue to apply cleanly to AI and exactly where AI's distinctive properties require them to be extended or qualified. This paper's integrated model is best understood as one attempt at that extension, synthesizing evidence that has so far accumulated largely within separate literatures, rather than as a wholesale replacement for the theoretical foundations strategic management has relied on for the past four decades.

The practical and theoretical implication is the same: strategic management researchers and practitioners alike should move past the general question of whether AI improves organizational performance, and take up the more specific and more tractable set of questions this paper's model makes available — **which pathway a given AI investment is intended to serve, whether the organization has built the capability that pathway requires, and whether the organization has resolved the decision-authority question that determines whether a technically superior AI output is actually permitted to change what the organization does.** Sustainable organizational performance, in both the durability sense and the ESG sense this paper has distinguished, depends on all three conditions holding together — and the evidence reviewed here suggests most organizations, and much of the strategic management literature evaluating them, have so far attended much more closely to the first two than to the third.



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Figure 1. An Integrated Model of AI-Enabled Strategic Management

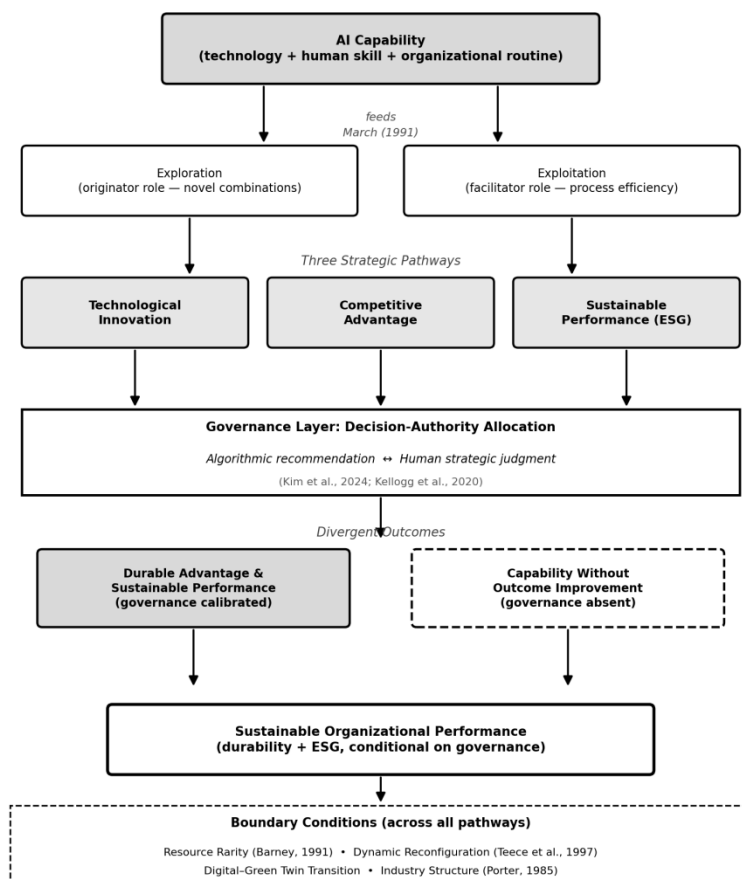


Figure 1. An Integrated Model of AI-Enabled Strategic Management, showing AI capability feeding parallel exploration and exploitation pathways toward competitive advantage and sustainable performance, conditioned throughout by decision-authority governance.



This model has a specific implication that distinguishes it from more generic accounts of “AI-driven strategy” common in the applied literature: because the three pathways share a common governance dependency, a firm's underinvestment in decision-authority governance does not merely limit one strategic outcome while leaving others intact; it constrains innovation, competitive advantage, and sustainable performance simultaneously, since all three depend on the same underlying condition. This shared dependency also explains a pattern this paper's review has surfaced repeatedly across otherwise disparate literatures — Kim et al.'s (2024) inspections evidence, Kellogg et al.'s (2020) algorithmic-control evidence, and algorithm-aversion findings from the adjacent accounting and auditing literature — all pointing toward the same underlying mechanism: technical capability and organizational decision quality are separable, and strategic management theory's historical emphasis on the former has left the latter comparatively undertheorized relative to its apparent empirical importance