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Rethinking Competitive Strategy for a World Driven by Intelligent Technologies

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ABSTRACT

This paper examines how intelligent technologies, including artificial intelligence, machine learning, predictive analytics, autonomous systems, robotics, digital twins, the Internet of Things, edge and cloud computing, knowledge graphs, large language models, decision intelligence, agentic AI, and cyber-physical systems, are changing the foundations of competitive strategy. Classical strategy theories, including the resource-based view, Porter's positioning framework, transaction cost economics, and dynamic capabilities, were built for environments in which human judgment, physical assets, and comparatively stable industry structures determined firm performance. Those assumptions hold less well once intelligent technologies become embedded in decision-making, learning, innovation, and value creation across the firm. Drawing on strategic management, information systems, and organizational theory research, this paper argues that classical frameworks remain partly valid but need conceptual extension rather than outright replacement. It develops an original model, the Intelligent Strategy Capability Framework (ISCF), which explains how lasting advantage arises from the interaction of strategic intelligence, human judgment, AI-augmented decision capability, organizational learning, digital resource orchestration, adaptive innovation, knowledge integration, platform and ecosystem strategy, trust and responsible AI, strategic agility, institutional adaptability, and governance capability. The paper discusses managerial and policy implications and sets out directions for future research on strategy in technology-intensive organizations. The central claim is that competitive advantage in an AI-enabled economy depends less on owning intelligent technology and more on the organizational capacity to combine machine intelligence with human judgment under conditions of fast diffusion and rising institutional scrutiny.

Keywords: Competitive strategy, artificial intelligence, dynamic capabilities, digital strategy, platform ecosystems, organizational learning, responsible AI governance

INTRODUCTION

Competitive strategy research has long rested on a set of working assumptions: that firms compete for scarce resources, that industry structure shapes profitability, and that managers, drawing on experience and judgment, choose positions and capabilities that rivals cannot easily copy. These assumptions produced durable theories. Porter's positioning framework explained how industry forces set the ceiling on average profitability (Porter, 1980, 1985). The resource-based view explained how firm-specific, hard-to-imitate resources produce advantage that persists over time (Barney, 1991). Dynamic capabilities theory explained how firms renew their resource base as conditions change (Teece, Pisano, & Shuen, 1997; Teece, 2007). Each of these accounts treated technology as one input among several, subject to managerial choice and organizational routine.

That treatment is no longer adequate. Intelligent technologies, a category that spans machine learning, predictive analytics, autonomous systems, robotics, digital twins, the Internet of Things, edge and cloud computing, knowledge graphs, large language models, decision intelligence platforms, agentic AI, and cyber-physical systems, do not simply automate existing tasks. They alter who or what makes a decision, how a firm learns from experience, how innovation is generated and tested, and how value moves between firms in networks that no longer resemble linear value chains (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Vial, 2019). Krakowski, Luger, and Raisch (2023) show, in a controlled study of chess competitions before and after the arrival of AI engines, that the introduction of a capable machine into a competitive domain triggers two processes at once: substitution, in which traditional human capabilities lose their value, and complementation, in which new sources of advantage appear at the interface between human and machine cognition. Their finding generalizes well beyond chess. Wherever intelligent systems enter a domain of skilled decision-making, the sources of competitive heterogeneity shift, and firms that continue to compete on the old basis of advantage find that basis eroding even as new, less visible advantages form around them.

This paper treats that shift as a problem for strategy theory rather than a matter of technology adoption. Firms have always adopted new technology, and strategy scholars have always debated its effects. What is different now is the scope and depth of the change. Intelligent technologies enter not one function but nearly every one: pricing, forecasting, quality control, recruitment, customer service, product design, logistics, risk assessment, and strategic planning itself. Raisch and Krakowski (2021) describe this as a persistent tension between automation, in which machines replace a human task, and augmentation, in which humans and machines perform a task together, and they argue that the two cannot be neatly separated in management practice; the same organization automates some tasks while augmenting others, often within the same process. That paradox has direct consequences for how a firm builds and defends competitive advantage, because it means the firm cannot choose a single technology strategy and apply it uniformly.

The paper proceeds as follows. Section 2 traces the evolution of competitive strategy thought from positioning through resources to dynamic capabilities and digital strategy. Section 3 reviews recent literature on intelligent technologies and firm performance. Section 4 sets out the theoretical foundations this paper draws on and critically compares their assumptions. Section 5 examines how intelligent technologies transform specific organizational capabilities. Section 6 identifies the changing sources of competitive advantage. Section 7 discusses where traditional strategic thinking runs into difficulty. Section 8 presents the paper's central contribution, the Intelligent Strategy Capability Framework. Sections 9 through 11 discuss managerial implications, policy and governance implications, and directions for future research, and Section 12 closes the paper.

EVOLUTION OF COMPETITIVE STRATEGY

Strategy research has moved through several dominant paradigms, each responding to the limitations of the one before it. The positioning school, associated most closely with Porter (1980, 1985), treated the firm as a unit that selects its place within an industry structure defined by five forces: the threat of new entrants, the bargaining power of buyers and suppliers, the threat of substitutes, and the intensity of rivalry among existing competitors. Advantage came from occupying a position, whether cost leadership, differentiation, or focus, that the structure of the industry allowed to be defended. The value chain (Porter, 1985) gave managers a tool for locating where in the firm's activities that advantage was created.

The positioning view assumed industry boundaries that were reasonably stable and observable, and it treated the firm largely as a black box whose internal capabilities mattered only in that they supported a chosen position. The resource-based view corrected this by turning attention inward. Barney (1991) argued that sustained competitive advantage requires resources that are valuable, rare, imperfectly imitable, and without close substitutes. Wernerfelt's (1984) earlier formulation and later refinements extended this logic to argue that firms are best understood as bundles of resources rather than as portfolios of product-market positions. The knowledge-based view built on the resource-based view by treating knowledge, and especially tacit knowledge embedded in routines and relationships, as the resource most resistant to imitation (Grant, 1996; Nonaka, 1994).

Both the positioning and resource-based traditions struggled to explain how firms adapt when their environment changes quickly. Dynamic capabilities theory addressed that gap. Teece, Pisano, and Shuen (1997) defined dynamic capabilities as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments, and Teece (2007) later specified the microfoundations of this ability in terms of sensing opportunities, seizing them through investment, and transforming the organization to sustain advantage. Eisenhardt and Martin (2000) offered a competing account in which dynamic capabilities are best understood not as vague, idiosyncratic routines but as identifiable, sometimes even simple, processes such as product development or alliance management, whose value lies in how they are combined rather than in their uniqueness. This disagreement about whether dynamic capabilities are firm-specific and hard to observe, or common and combinable, remains unresolved and matters directly for how one thinks about AI-related capabilities, since AI tools themselves are widely available while the organizational routines for using them well are not.

Digital strategy research emerged as a further response to a specific limitation in these classical accounts: their treatment of information technology as a support function rather than as constitutive of strategy itself. Bharadwaj, El Sawy, Pavlou, and Venkatraman (2013) argued that the traditional view, in which IT strategy is aligned with but subordinate to business strategy, no longer describes firms whose products, processes, and customer relationships are themselves digital. They proposed the term digital business strategy to capture this fusion. Vial (2019), reviewing several hundred studies, organized the digital transformation literature into a model that links digital technologies, the strategic responses they provoke, and the organizational and societal impacts that follow, and he stressed that the disruptions technology creates are as often social and organizational as they are technical.

Platform and ecosystem theory represents the most recent major addition to this line of development. Jacobides, Cennamo, and Gawer (2018) distinguish ecosystems from markets and hierarchies by their reliance on non-generic complementarities: sets of firms coordinate through shared technical or contractual roles without full ownership or control by any single party. This reframing matters for intelligent technologies because AI capabilities, data assets, and computing infrastructure are frequently supplied and consumed across firm boundaries rather than owned outright, so that a firm's competitive position depends as much on its place within an ecosystem of complementors as on its internal resources.

Read together, this progression from positioning to resources to dynamic capabilities to digital and ecosystem strategy shows a field that has repeatedly had to expand its unit of analysis, from the industry, to the firm, to the firm's capacity for change, to the firm's digital and relational context. Intelligent technologies press that expansion further still, because they introduce a new kind of actor, the algorithmic system, into decision processes that strategy theory has always assumed were exclusively human.

LITERATURE REVIEW

Research directly addressing artificial intelligence and firm strategy has grown quickly since the early 2020s, following a period in which AI was treated mainly as an operational or IT topic. Kaplan and Haenlein (2020) set an early agenda by describing AI adoption as a governance and organizational challenge as much as a technical one, noting that the same tools that improve efficiency also raise new questions about accountability and control. Shrestha, Krishna, and von Krogh (2021) examined how deep learning changes organizational decision-making, arguing that algorithmic recommendations differ from human judgment in ways that create both promise and difficulty: machine predictions can process far larger information sets than any individual manager, but the resulting outputs are often opaque, which complicates the deliberation and justification that organizational decision-making has traditionally required.

Raisch and Krakowski (2021) contributed one of the field's most cited theoretical statements by identifying the automation-augmentation paradox. Reviewing several influential management books on AI, they rejected the simple prescription that firms should favor augmentation over automation, arguing instead that the two are interdependent across time and across the organization: a task that is augmented today may be automated tomorrow once the pattern of human-machine interaction has been learned, and a fully automated process still depends on humans to design, monitor, and correct it. This reframing has proven useful because it explains why firms cannot resolve their AI strategy once and treat it as settled; the relationship between human and machine work continues to move.

Krakowski, Luger, and Raisch (2023) extended this line of reasoning with an empirical study that used chess as a controlled setting for observing competitive dynamics under AI adoption. Comparing player performance across conventional tournaments, centaur tournaments in which humans use AI assistance, and pure engine competitions, they found that AI adoption triggers substitution and complementation together rather than one or the other, eroding some traditional sources of human advantage while opening new ones tied to how well a person works with a machine partner. Their resource-based interpretation of these findings, that AI changes which resources are valuable, rare, and hard to imitate rather than simply adding a new resource to an existing list, is directly relevant to the argument developed in this paper.

Related work has examined the organizational conditions under which AI's productive effects appear. Jia, Luo, Fang, and colleagues (2024), publishing in the Academy of Management Journal, studied the conditions under which AI use increases employee creativity, finding that the relationship is not automatic and depends on how AI is introduced into the workflow and on the kind of tasks involved. Vomberg and colleagues (2023) studied firms attempting to build AI-driven products from a cold start, showing that the network effects on which many AI products depend create a distinct strategic problem, since the value of a predictive system typically grows with the volume and variety of data it can draw on, which gives early movers in data accumulation a durable if not permanent edge.

Research on digital and platform strategy provides a second relevant stream. Vial's (2019) review situates digital transformation as a process with antecedents, mechanisms, and impacts rather than a single event, a framing that resists the tendency in practitioner writing to treat AI adoption as a discrete project with a defined endpoint. Jacobides, Cennamo, and Gawer (2018) supply the vocabulary needed to describe how intelligent technologies reorganize industry boundaries: where an ecosystem's non-generic complementarities involve data, model, or algorithmic assets, the identity of the ecosystem's central orchestrator, and the terms on which other firms can participate, become strategic questions in their own right.

A third stream addresses governance and responsibility. Because intelligent systems, once deployed, can act with a degree of autonomy that earlier organizational technologies did not have, questions of accountability, fairness, and oversight have moved from the periphery of strategy discussions to the center. Policy instruments such as the OECD's Principles on Artificial Intelligence (OECD, 2019) and the United States National Institute of Standards and Technology's AI Risk Management Framework (NIST, 2023) formalize expectations around transparency, robustness, and accountability that firms must now treat as strategic constraints rather than as compliance afterthoughts.

Across these streams, a common thread emerges: the AI-strategy literature has moved past treating artificial intelligence as a general productivity tool and has begun to ask how, specifically, it changes the mechanisms by which advantage is created and sustained. This paper builds on that literature by proposing an integrative framework that connects these separate findings, on substitution and complementation, on automation and augmentation paradoxes, on ecosystem participation, and on governance, into a single account of firm-level strategic capability.

THEORETICAL FOUNDATIONS

This section examines the classical theories most relevant to the paper's argument, states their central claims, and identifies where intelligent technologies place pressure on their assumptions.

Resource-based view. Barney's (1991) framework holds that advantage persists when a resource is valuable, rare, imperfectly imitable, and non-substitutable. The framework's strength lies in its clarity and its wide applicability across industries. Its limitation, as Krakowski and colleagues (2023) demonstrate, is that it assumes a relatively fixed inventory of resource types, mainly physical, financial, human, and organizational. Intelligent technologies complicate this inventory in two ways. First, AI models and the data that train them behave like resources whose value depends on volume, freshness, and proprietary access, properties that do not map cleanly onto Barney's original categories. Second, AI-based systems can themselves generate new resources, in the form of learned patterns or predictive capability, faster than firms can accumulate resources through conventional means, which shortens the time over which any single resource advantage might be expected to hold.

Knowledge-based view. Grant (1996) and Nonaka (1994) treat knowledge, and especially tacit knowledge that resists codification, as the resource most protected from imitation. Intelligent technologies challenge this assumption directly, because large language models and knowledge graphs are, in effect, engines for codifying knowledge that was previously tacit. When a model can approximate the pattern recognition of an experienced professional, the protective value of that professional's tacit knowledge weakens. At the same time, new tacit knowledge forms around the skill of working productively with these systems, of framing problems in ways a model can act on and of interpreting its outputs critically, so that the knowledge-based view remains useful but needs to be applied to a different, higher layer of expertise.

Dynamic capabilities. Teece's (2007) sensing, seizing, and transforming sequence describes how firms adapt over time, and this sequence maps well onto how firms must approach intelligent technologies: sensing which AI applications are relevant to the firm's context, seizing them through investment and pilot deployment, and transforming organizational routines and structures to make the investment pay off. The debate between Teece (2007), who treats these capabilities as firm-specific and difficult to imitate, and Eisenhardt and Martin (2000), who treat them as identifiable and combinable processes, becomes especially pointed with AI, because the underlying models and cloud infrastructure are often available to any competitor with sufficient budget, which would seem to support the Eisenhardt and Martin view, while the organizational routines for using these tools effectively, the sequencing of pilots, the governance of data, the retraining of staff, remain closer to the Teece account of tacit, path-dependent capability. Both views appear partly correct, and this paper's proposed framework treats AI-augmented decision capability and organizational learning as the layer where firm-specific advantage actually forms, above a layer of widely accessible technology.

Transaction cost economics. Williamson's (1985) framework explains firm boundaries by the relative cost of coordinating an activity through markets versus internal hierarchy, driven mainly by asset specificity, uncertainty, and the frequency of exchange. Intelligent technologies reduce some coordination costs sharply, since AI-based matching, forecasting, and contract monitoring can substitute for functions that previously required dedicated internal staff, which should in principle push more activity toward markets. Ecosystem and platform arrangements complicate this prediction, because they represent a coordination form that is neither market nor hierarchy, held together instead by shared technical standards and data-sharing agreements (Jacobides et al., 2018). Transaction cost logic still applies within these arrangements, but the boundary question it was designed to answer, whether an activity sits inside or outside the firm, becomes less binary once so much coordination happens through shared algorithmic infrastructure that no single firm fully controls.

Competitive positioning and value chain theory. Porter's (1980, 1985) five forces and value chain remain useful for mapping where value is created and captured, and this paper does not set them aside. Their limitation is that both assume a value chain with a broadly linear structure, from inbound logistics through operations to outbound logistics, marketing, and service. Intelligent technologies, especially when embedded in platform ecosystems, replace parts of this linear structure with a networked structure in which value is created through combinations of complementary contributions from multiple firms at once, so that the five forces analysis, performed at the level of a single industry, risks missing where the more important competitive pressure originates, often from an adjacent ecosystem rather than from a direct product competitor.

Blue ocean strategy. Kim and Mauborgne (2005) argue that lasting advantage comes less from competing within an existing structure and more from creating a new market space where competition is, for a time, irrelevant. Intelligent technologies open new such spaces regularly, since a predictive or generative capability can create demand for a product category that did not previously exist. The framework's limitation in this context is that it offers little guidance on how quickly a newly created space will itself become contested once the underlying AI capability diffuses to competitors, a question this paper addresses directly in Section 6.

Institutional theory. DiMaggio and Powell (1983) explain why organizations in a field tend to resemble one another over time, through coercive, mimetic, and normative pressures. This pattern is visible in AI adoption, where firms frequently adopt similar tools and vendor platforms less because those tools fit their specific context and more because doing so signals legitimacy to investors, regulators, and customers. Institutional theory therefore helps explain a puzzle that resource-based logic alone cannot: why many firms in the same industry converge on similar AI investments even though, by resource-based reasoning, imitation should erode any advantage those investments might offer.

Complex adaptive systems and organizational learning. Firms embedded in AI-enabled ecosystems increasingly resemble complex adaptive systems, in which the actions of many interacting agents, human and algorithmic, produce outcomes that are not fully predictable from the properties of any single agent. Organizational learning theory and absorptive capacity, in particular Cohen and Levinthal's (1990) account of a firm's ability to recognize, assimilate, and apply new external knowledge, remain central here, because a firm's capacity to learn from the continuous stream of data an AI system generates depends on prior related knowledge within the organization, exactly as Cohen and Levinthal describe for any external knowledge source.

Behavioral theory of the firm and stakeholder theory. Cyert and March's (1963) behavioral account, which treats the firm as a coalition with bounded rationality and satisficing rather than optimizing behavior, offers a useful corrective to overly rationalist accounts of AI adoption; real organizations adopt AI under political constraints, budget cycles, and incomplete information, not as a clean optimization exercise. Freeman's (1984) stakeholder theory becomes more, not less, relevant in this setting, because intelligent systems affect employees, customers, communities, and regulators in ways that a purely shareholder-focused strategy calculus will tend to miss, particularly where algorithmic decisions touch employment, credit, or safety.

Digital strategy and platform ecosystem theory. As discussed in Section 2, Bharadwaj and colleagues (2013) and Vial (2019) supply the account of how IT strategy fuses with business strategy, while Jacobides and colleagues (2018) supply the account of ecosystem governance. Both are treated in this paper as necessary but not sufficient: they describe the structural conditions under which intelligent technologies operate but do not, on their own, explain how a specific firm builds the internal capability to act well within those conditions. That is the gap the Intelligent Strategy Capability Framework, presented in Section 8, is intended to close.

Responsible AI governance. Emerging governance frameworks, including the OECD's (2019) AI Principles and the NIST (2023) AI Risk Management Framework, formalize expectations of transparency, accountability, robustness, and fairness. These frameworks are not strategy theories in the academic sense, but they function as an increasingly binding constraint on strategic choice, in the way that environmental and safety regulation constrained strategic choice in earlier decades, and this paper treats responsible AI governance as a strategic capability rather than solely a compliance function.

Taken together, these theories remain valuable in describing the pieces of the picture, resources, knowledge, capabilities, transaction costs, position, market creation, institutional pressure, learning, coalition behavior, stakeholder claims, digital fusion, ecosystem structure, and governance. None of them, taken alone, explains how these pieces interact once intelligent technologies are present throughout the firm. That synthesis is the task Section 8 undertakes.

INTELLIGENT TECHNOLOGIES AND STRATEGIC TRANSFORMATION

Intelligent technologies affect strategy by changing four organizational processes that earlier theory largely treated as stable: decision-making, learning, innovation, and value creation.

Decision-making. Strategic decisions have traditionally combined data, experience, and judgment, with judgment doing most of the work in conditions of uncertainty where data is thin. Predictive analytics and decision intelligence platforms shift this balance by supplying probabilistic forecasts across a wider range of scenarios than a human planning team could generate unassisted. Shrestha, Krishna, and von Krogh (2021) note that this shift creates a genuine improvement in the range of options considered, but it also introduces a dependency on model outputs whose internal logic managers frequently cannot fully inspect, a condition sometimes called the transparency problem. Agentic AI systems, which can take a sequence of actions toward a goal with limited human intervention at each step, extend this shift further, since the decision is no longer a discrete event that a human approves but a continuing process the system executes, with human oversight applied at intervals rather than at every step.

Organizational learning. Classical organizational learning theory describes learning as a cycle in which the firm acts, observes outcomes, and revises its routines. Intelligent systems compress this cycle by generating and processing feedback continuously rather than at the pace of quarterly reviews or annual audits. A firm using machine learning models in pricing, for instance, can observe the effect of a price change within hours rather than months. This compression raises the value of absorptive capacity (Cohen & Levinthal, 1990), since a firm that lacks the internal expertise to interpret a fast stream of model output gains little advantage from having that stream available, while a firm with strong absorptive capacity can turn the same data into a durable improvement in judgment.

Innovation. Product and process innovation increasingly depends on the interaction between human creativity and machine-generated options. Generative AI systems can produce large numbers of design variants, molecular structures, code fragments, or marketing concepts, which changes the innovation bottleneck from generating candidate ideas to evaluating and selecting among them. Jia and colleagues (2024) find that this shift benefits creativity only under particular conditions, generally where employees retain a meaningful role in framing the problem and judging the output rather than treating the AI system as a source of finished answers. This finding matters for strategy because it implies that firms cannot buy innovation capability off the shelf by purchasing generative AI licenses; the capability depends on how the tool is embedded into existing creative and evaluative routines.

Value creation and ecosystem participation. Perhaps the deepest change concerns where value is created and who captures it. Traditional value chains assumed value moved in a largely linear sequence from raw input to finished product. Intelligent technologies, especially when tied to platform infrastructure, allow value to be created through combinations of complementary contributions supplied by different firms at once, exactly the structure Jacobides, Cennamo, and Gawer (2018) describe as an ecosystem built around non-generic complementarities. A firm's data, model, and algorithmic assets often generate more value when combined with a partner's complementary assets than when used alone, which means competitive strategy increasingly involves choosing an ecosystem position, orchestrator, complementor, or something in between, rather than simply choosing a product-market position within a single industry.

Examples from well-known firms illustrate these mechanisms without needing to be treated as case studies in the formal sense. Amazon's recommendation and logistics systems depend on continuous learning from purchase and delivery data at a scale few competitors can match, which supports the durability of its advantage even though the underlying algorithmic techniques are broadly known. NVIDIA's position rests less on any single chip design and more on an ecosystem of software, developer tools, and partner relationships built around its hardware, a structure closer to Jacobides and colleagues' ecosystem logic than to a conventional product-market position. Siemens and Toyota have both used digital twins, virtual replicas of physical assets updated continuously with sensor data, to compress the learning cycle in manufacturing, turning what used to be periodic quality reviews into ongoing model-based monitoring. These examples support the paper's broader claim: intelligent technologies do not simply speed up existing processes, they change which processes generate advantage in the first place.

CHANGING SOURCES OF COMPETITIVE ADVANTAGE

Building on the theoretical review and the transformation mechanisms above, this section identifies four sources of competitive advantage that intelligent technologies bring into being or substantially reshape.

Data and model assets as a distinct resource category. Data and the models trained on it behave differently from the resource categories Barney (1991) originally described. Their value depends on scale, since predictive accuracy commonly improves with more training data up to a point, and on proprietary access, since data collected through unique customer or operational relationships cannot easily be replicated by a competitor. Vomberg and colleagues (2023) describe the resulting cold-start problem: a firm entering an AI-dependent market late faces a data disadvantage that is difficult to close through capital investment alone, because data accumulates through use over time rather than being purchased outright. This creates a form of first-mover advantage distinct from the brand or scale advantages classical strategy theory has traditionally emphasized.

Human-machine complementarity as a renewable source of advantage. Krakowski, Luger, and Raisch (2023) show that even as AI substitutes for some traditional human capabilities, it opens new sources of advantage tied to how effectively humans and machines work together. This complementarity advantage differs from earlier resource advantages in an important respect: it is renewable rather than fixed, because the skill of working productively with an evolving set of AI tools must be continually rebuilt as the tools themselves change, which means firms cannot simply acquire this advantage once and hold it, as they might a patent or a piece of physical infrastructure.

Learning velocity. Where classical organizational learning theory treated learning speed as roughly similar across firms in an industry, intelligent technologies make learning velocity itself a source of differentiation. A firm whose systems and staff can absorb, interpret, and act on model output faster than its rivals compounds small advantages into larger ones over time, in the same way Cohen and Levinthal (1990) describe absorptive capacity compounding a firm's capacity to exploit externally generated knowledge.

Ecosystem position. As Section 5 discussed, a firm's place within a platform ecosystem, whether as an orchestrator that sets the terms of participation or as a complementor that depends on another firm's platform, has become a source of advantage in its own right, separate from the firm's standing within its own product-market industry (Jacobides et al., 2018). A firm can hold a strong resource-based position within its industry and still be strategically vulnerable if it occupies a weak position within the ecosystem its industry depends on.

Trust and responsible AI as a differentiator. As algorithmic decision-making touches customers, employees, and regulators more directly, a firm's demonstrated ability to deploy AI responsibly, transparently, and fairly becomes a differentiator in its own right rather than merely a defensive compliance measure. Firms that can show customers and regulators a credible governance record around their AI use gain access to markets, partnerships, and talent that firms without that record cannot easily reach, a pattern already visible in sectors such as healthcare and financial services where the NIST (2023) and OECD (2019) frameworks are becoming reference points for procurement decisions.

These four sources, data and model assets, human-machine complementarity, learning velocity, and ecosystem position, together with the newer role of trust, do not replace the classical sources of advantage identified by the resource-based view and dynamic capabilities theory. They sit alongside them, and in many firms they now matter more.

CHALLENGES TO TRADITIONAL STRATEGIC THINKING

Several assumptions embedded in traditional strategy models require revision considering the mechanisms discussed above.

The assumption of stable industry boundaries. Five forces analysis assumes an industry with reasonably clear boundaries, whether the industry is retail, banking, or automobiles. Platform ecosystems built around intelligent technologies frequently cut across these boundaries, since a data or model asset developed for one purpose can be redeployed in an entirely different industry with modest adaptation. A firm performing a standard five forces analysis within its own industry can miss the more consequential competitive threat arriving from outside that industry altogether.

The assumption that imitation takes time. Classical resource-based logic assumes that imitating a valuable resource takes time and effort, which is precisely what allows a temporary advantage to become sustained. Intelligent technologies can compress this imitation lag substantially, since a competitor with sufficient capital can often purchase comparable machine learning infrastructure and cloud computing capacity within a matter of months. Advantage, where it persists at all, tends to shift from the technology itself toward the organizational routines surrounding its use, exactly the layer Teece (2007) treats as harder to imitate than the underlying technology.

The assumption that decisions are made by identifiable human agents. Stakeholder theory, behavioral theory of the firm, and institutional theory all assume that organizational decisions trace back to identifiable human decision-makers who can be held accountable for them. Agentic AI systems complicate this assumption, since a sequence of actions taken by an autonomous system toward a broadly specified goal does not always map cleanly onto a single human decision, which raises real questions of accountability that existing theory did not need to address in earlier periods.

The assumption that learning is periodic. Organizational learning theory has generally described learning as occurring through discrete cycles, project reviews, annual strategic planning, occasional restructuring. Continuous data streams from intelligent systems make learning a constant background process rather than an episodic one, which strains planning and budgeting cycles designed around annual or quarterly rhythms and calls for governance structures that can respond to signals arriving far more frequently than those cycles allow.

The assumption that value chains are linear. As discussed above, value chain theory (Porter, 1985) assumes activities proceed in a broadly linear sequence. Ecosystem-based value creation, built around the non-generic complementarities Jacobides and colleagues (2018) describe, does not fit this sequence well, since value depends on the simultaneous combination of contributions from multiple firms rather than on a sequence of value-adding steps within one firm.

The assumption that competitive advantage can be sustained rather than continually renewed. Perhaps the deepest challenge concerns the very idea of sustained competitive advantage. Classical theory, including Barney's (1991) resource-based view, envisions a state in which a firm secures an advantage and defends it over an extended period. Where intelligent technologies diffuse quickly across an industry, and where the underlying infrastructure is available to any well-funded competitor, advantage looks less like a state to be defended and more like a capability to be continually rebuilt, closer to Eisenhardt and Martin's (2000) account of dynamic capabilities as a process than to Barney's account of a defensible resource position.

These challenges do not mean the classical theories are wrong. They mean the theories describe conditions that hold only partially, or only for a limited period, once intelligent technologies are present throughout an organization's operations. The framework proposed in the next section is built to accommodate this partial validity rather than to discard the classical theories altogether.

THE INTELLIGENT STRATEGY CAPABILITY FRAMEWORK (ISCF)

The preceding sections established that classical strategy theories remain useful for describing individual pieces of firm behavior, resource accumulation, capability renewal, industry positioning, and market creation, but that none of them, on its own, explains how a firm builds and sustains advantage when intelligent technologies are embedded throughout its operations. This section introduces the Intelligent Strategy Capability Framework (ISCF) as this paper's original contribution, intended to close that gap.

Overview of the framework

The ISCF proposes that sustainable competitive advantage in technology-intensive environments emerges from the ongoing interaction of twelve capability dimensions, organized into four layers.

The first layer, the sensing and judgment layer, comprises **strategic intelligence** and **human judgment**. Strategic intelligence refers to the firm's capacity to gather, integrate, and interpret signals about its competitive environment from both traditional sources and algorithmic ones. Human judgment refers to the capacity of managers and employees to apply experience, ethical reasoning, and contextual understanding to situations that data alone cannot resolve, a capacity that remains necessary even as, or especially as, machine intelligence expands.

The second layer, the augmentation and learning layer, comprises **AI-augmented decision capability**, **dynamic organizational learning**, and **digital resource orchestration**. AI-augmented decision capability describes the firm's ability to combine algorithmic outputs with human judgment in a way that improves decisions without surrendering accountability for them. Dynamic organizational learning extends Cohen and Levinthal's (1990) absorptive capacity to the continuous data streams intelligent systems generate. Digital resource orchestration describes the firm's ability to combine data, computing infrastructure, and talent into working systems, extending Teece's (2007) sensing-seizing-transforming sequence to the specific case of digital and AI assets.

The third layer, the innovation and integration layer, comprises **adaptive innovation**, **knowledge integration**, and **platform and ecosystem strategy**. Adaptive innovation captures the shift, discussed in Section 5, from idea generation to evaluation and selection as the primary innovation bottleneck. Knowledge integration describes the firm's ability to combine tacit human expertise with codified machine knowledge, extending Grant's (1996) knowledge-based view to a setting where knowledge now exists in both human and algorithmic form. Platform and ecosystem strategy applies Jacobides, Cennamo, and Gawer's (2018) ecosystem logic to the firm's specific choices about orchestration, complementorship, and participation terms.

The fourth layer, the trust and adaptability layer, comprises **trust and responsible AI**, **strategic agility**, **institutional adaptability**, and **governance capability**. Trust and responsible AI reflects the discussion in Section 6 of governance as a differentiator rather than a constraint alone. Strategic agility describes the firm's capacity to reallocate resources and revise strategy quickly as intelligent technologies and their competitive implications continue to change. Institutional adaptability extends DiMaggio and Powell's (1983) account of field-level pressures to the specific dynamics of AI adoption, where legitimacy concerns often drive adoption decisions independent of proven return on investment. Governance capability describes the firm's structures for oversight, accountability, and risk management around its use of intelligent systems, drawing on the OECD (2019) and NIST (2023) frameworks discussed above.

How the dimensions reinforce one another

The ISCF's central claim is that these twelve dimensions are mutually reinforcing rather than independent, and that competitive advantage depends on their combination rather than on any single dimension considered alone.

Strategic intelligence supplies the raw signals that AI-augmented decision capability processes, but the value of those signals depends on human judgment to frame the questions correctly and to catch cases where a model's output does not fit the situation, exactly the condition Shrestha, Krishna, and von Krogh (2021) describe as the interpretive burden that remains with human decision-makers even as machine processing power grows. Dynamic organizational learning feeds on the outputs of AI-augmented decisions, and its effectiveness depends on digital resource orchestration to ensure the data and computing infrastructure needed for learning are actually available where and when they are needed. Adaptive innovation depends on knowledge integration, since generative tools produce more valuable output when guided by codified domain knowledge and interpreted through tacit human expertise together, a pairing Jia and colleagues (2024) identify as a condition for AI to support rather than undermine creativity.

Platform and ecosystem strategy connects the innovation layer to the trust and adaptability layer, since a firm's choice of ecosystem position shapes and is shaped by its governance obligations; an orchestrator firm typically bears greater governance responsibility for the ecosystem's algorithmic behavior than a complementor does, which in turn affects the trust the ecosystem's members and customers place in it. Strategic agility depends on the learning and innovation layers functioning well, since a firm cannot reallocate resources quickly toward a promising new AI application if its organizational learning processes have not yet identified that the application is promising. Institutional adaptability and governance capability, finally, feed back into strategic intelligence, since a firm's understanding of the regulatory and normative environment it operates in is itself a form of strategic signal that shapes which AI investments are viable.

This circular structure means the ISCF does not describe a linear process that a firm completes once. It describes an ongoing set of interactions among capabilities that must be continually maintained and rebalanced, consistent with the paper's broader argument in Section 7 that sustained advantage in this setting looks more like continual renewal than like a defended position.

Illustrating the framework

Consider a firm applying the ISCF to a predictive maintenance initiative built on sensor data and digital twin technology, an approach already used by manufacturers such as Siemens. Strategic intelligence identifies which equipment failures carry the highest cost and where sensor data could plausibly predict them. Human judgment determines which of the many statistically detectable patterns are worth acting on, since not every correlation a model surfaces reflects a mechanism engineers should trust. AI-augmented decision capability translates model predictions into maintenance schedules while keeping a technician's sign-off in the loop for high-stakes interventions. Dynamic organizational learning captures the outcomes of each intervention, correct predictions, false alarms, and missed failures alike, and feeds them back into the model and into the judgment of the engineering team. Digital resource orchestration ensures the sensor network, cloud storage, and computing capacity needed to run this cycle are actually available at the plant level, not just in a central data science team. Adaptive innovation might apply the same digital twin infrastructure to a new product line once its value in maintenance is proven. Knowledge integration combines the codified statistical patterns the model has learned with the tacit knowledge of veteran engineers about how specific machines actually fail. Platform and ecosystem strategy determines whether the firm builds this capability entirely in-house or draws on a partner's industrial IoT platform, a choice with direct consequences for how much of the resulting advantage the firm alone can capture. Trust and responsible AI governs how the firm explains a maintenance-related decision to a customer or regulator if a failure does occur despite the system's prediction. Strategic agility determines how quickly the firm can extend this initiative to other plants once it proves valuable at the first one. Institutional adaptability and governance capability shape whether the firm's approach meets the expectations of an industry increasingly attentive to algorithmic accountability.

This single example shows how the twelve dimensions function together in a concrete setting, rather than as an abstract list. The framework's contribution to strategic management theory lies in specifying these dimensions and their connections explicitly, in a form that can guide both further empirical research and managerial practice, where earlier frameworks addressed pieces of this picture without integrating them.

MANAGERIAL IMPLICATIONS

The ISCF carries several direct implications for practicing managers.

First, firms should treat AI-augmented decision capability, dynamic organizational learning, and digital resource orchestration as capabilities to be built deliberately rather than as automatic consequences of purchasing AI tools. Vomberg and colleagues' (2023) finding on the cold-start problem in AI strategy suggests that firms which delay building these capabilities face a compounding disadvantage that later investment cannot easily reverse.

Second, managers should expect the balance between automation and augmentation to shift continually within their organization rather than settling into a fixed pattern, following Raisch and Krakowski's (2021) account of this relationship as a persistent paradox rather than a problem to be solved once. Governance structures should be designed to review this balance regularly rather than treating an initial automation-augmentation decision as final.

Third, firms should assess their ecosystem position as carefully as they assess their product-market position, since Jacobides, Cennamo, and Gawer's (2018) ecosystem logic implies that a strong industry position can coexist with a weak ecosystem position, and vice versa. This assessment should include an honest appraisal of whether the firm is positioned as an orchestrator or a complementor within the platforms its data and AI capabilities depend on.

Fourth, investment in generative and predictive AI tools should be paired with deliberate attention to knowledge integration, since Jia and colleagues' (2024) findings suggest that AI tools improve creative and analytical output mainly when employees retain a substantive role in framing problems and evaluating output, not when tools are treated as replacements for that role.

Fifth, trust and responsible AI should be treated as a source of competitive differentiation and market access rather than solely as a compliance cost. Firms that build credible governance practices around their AI use, aligned with frameworks such as the NIST (2023) AI Risk Management Framework, position themselves for partnerships, procurement relationships, and regulatory relationships that firms without such practices may find closed to them.

Sixth, managers should recognize that the classical strategy tools they already know, the resource-based view, five forces analysis, and dynamic capabilities assessment, remain useful diagnostic instruments. The ISCF does not ask managers to discard these tools. It asks them to supplement industry and resource analysis with an explicit assessment of the twelve capability dimensions identified above, particularly where a competitor's threat may originate from an ecosystem position or an AI-driven capability that a conventional five forces analysis would not surface.

POLICY AND GOVERNANCE IMPLICATIONS

The rise of intelligent technologies as a strategic factor carries implications for policymakers and regulators as well as for firms.

Governance frameworks such as the OECD's (2019) Principles on Artificial Intelligence and the NIST (2023) AI Risk Management Framework represent an early stage in a broader institutionalization of AI governance, comparable in some respects to the gradual institutionalization of environmental and financial regulation in earlier decades. As these frameworks mature, firms that treat governance capability as a core strategic dimension, consistent with the fourth layer of the ISCF, will be better positioned to meet emerging regulatory expectations than firms that treat governance as an afterthought applied only once a deployed system draws scrutiny.

Policymakers face a related challenge in balancing the goal of encouraging innovation with the goal of protecting individuals and markets from the risks intelligent systems introduce, including risks to employment, to fair access to credit and services, and to market competition where a small number of firms control the data and computing infrastructure on which most AI applications depend. The ecosystem logic set out by Jacobides, Cennamo, and Gawer (2018) is directly relevant here, since regulatory attention focused only on individual firms may miss anti-competitive dynamics that arise instead at the level of the ecosystem, in the terms an orchestrator sets for its complementors.

Institutional theory (DiMaggio & Powell, 1983) suggests that firms will often adopt AI governance practices for reasons of legitimacy as much as for their proven effect on outcomes, which implies that policy frameworks with clear, verifiable standards, rather than vague principles alone, are more likely to produce meaningful change in firm behavior than frameworks that leave compliance largely to firm discretion.

FUTURE RESEARCH DIRECTIONS

Several questions raised in this paper call for further empirical study.

Research is needed on how the twelve dimensions of the ISCF can be measured at the firm level, since the framework as presented here is conceptual and would benefit from validated survey instruments or archival measures that allow researchers to test its claims about which combinations of dimensions predict performance.

Longitudinal research, following firms over multiple years as they adopt intelligent technologies, would help clarify whether the advantages described in Section 6, data and model assets, human-machine complementarity, learning velocity, ecosystem position, and trust, behave as this paper suggests, with some depreciating quickly through diffusion and others compounding over time.

Comparative research across industries would help establish whether the ISCF applies uniformly or whether particular dimensions matter more in some settings than others, for instance whether trust and responsible AI carries more weight in regulated industries such as healthcare and financial services than in less regulated ones.

Research connecting the ISCF to firm performance outcomes, profitability, market share, innovation output, and resilience during disruption, would help establish the framework's predictive validity beyond the conceptual argument developed here.

Finally, research on the boundary conditions of human-machine complementarity, following the direction opened by Krakowski, Luger, and Raisch (2023) and Jia and colleagues (2024), would help clarify under what conditions augmentation produces genuine advantage rather than merely shifting where errors and biases originate within a decision process.

CONCLUSION

This paper has argued that intelligent technologies change the foundations of competitive strategy by altering decision-making, organizational learning, innovation, and value creation rather than by simply adding a new productivity tool to the firm's existing operations. Classical strategy theories, the resource-based view, dynamic capabilities, transaction cost economics, competitive positioning, and blue ocean strategy among them, remain valuable for describing individual pieces of firm behavior, but none fully explains how a firm builds and sustains advantage once intelligent technologies are embedded throughout its operations. The Intelligent Strategy Capability Framework developed in this paper proposes that advantage in this setting depends on twelve interacting capability dimensions spanning sensing and judgment, augmentation and learning, innovation and integration, and trust and adaptability. The framework suggests that firms which treat these dimensions as capabilities to be deliberately built and continually renewed, rather than as consequences of technology purchase, are better positioned to compete as intelligent technologies continue to diffuse across industries. The central message for both scholars and practitioners is that competitive advantage in an AI-enabled economy rests less on possessing intelligent technology and more on the organizational capacity to combine machine intelligence with human judgment, learning, and accountability under conditions that will keep changing.

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