

Research Article

Algorithmic Competitive Advantage under Institutional Constraint: Data, Orchestration, and Complementary Capabilities in Resource-Constrained Economies

Seeratus Sabah* and Nahida Akhter Naiema

Department of General Management, School of Business and Entrepreneurship, Independent University Bangladesh, Dhaka, Bangladesh; nahidaakhter20sbe@iub.edu.bd (N.A.N.)

* Correspondence: s.sabah@iub.edu.bd (S.S.)

Abstract: Artificial intelligence is altering the competitive advantage by lowering the cost of prediction. Strategic management, however, knows little how this transformation unfolds where the institutions that supply advantage's complements are themselves underdeveloped. Current study is an integrative conceptual review connecting the resource-based view, dynamic capabilities, the economics of artificial intelligence, research on human–AI complementarity, and the institution-based view. It advances two arguments. First, as general-purpose predictive technologies diffuse and converge across competitors, generic predictive capability is commoditized and competitive advantage relocates to complements that resist imitation. These include strategically embedded data assets, managerial judgment encoded in decision architectures, and the orchestration of human and algorithmic agents. Second, and centrally, the accumulation and appropriation of these complements are conditioned by the institutional and infrastructural environment. Data infrastructure, factor markets for specialized talent, property-rights and appropriability regimes, and information intermediaries each moderate a specific link in the pathway from algorithmic resources to advantage. The study therefore theorizes resource-constrained economies not as disadvantaged versions of advanced economies but as boundary conditions that reveal, with unusual clarity, the mechanisms linking algorithmic resources to advantage. There are theses that cheap artificial intelligence (AI) democratizes advantage and enables developing-economy firms to leapfrog and that it structurally widens the gap between rich and poor economies. Current study, however, argues that the binding constraint shifts from access to algorithms, which diffuse cheaply as general-purpose tools, to complementary capabilities whose accumulation is institutionally gated. Hence the two theses operate at different levels of analysis and reconcile once access and advantage are distinguished. Seven propositions specify these relationships in causal, testable form, defining the multidimensional construct of the resource-constrained institutional environment, operationalizing artificial-intelligence orchestration capability, and identifying the conditions under which firms either experience constrained value creation or convert institutional voids into proprietary capability and defensible position. The framework contributes to competitive advantage theory by respecifying the scarcity structure that underpins advantage in the algorithmic firm; to the micro foundations program by relocating the explanatory locus from human action to human–algorithm interaction; and to the institution-based view by showing that institutions govern not only the adoption of artificial intelligence but the conversion of algorithmic resources into appropriated advantage.

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1. Introduction

Strategic management is organized around a single, enduring question of why do some firms attain and sustain superior performance while others facing ostensibly similar conditions do not (Rumelt, Dan and David 1994). For more than six decades, the field has answered by successively relocating the source of advantage from the early design and planning traditions (Andrews 1971; Ansoff 1965; Chandler 1962) and the counter-argument that strategy is substantially emergent rather than deliberately planned (Mintzberg 1978, 1994), to industry structure (Porter 1980), to firm-specific resources (Barney 1991), to organizational knowledge (Grant 1996), to the higher-order

capacity to reconfigure resources under change (Teece, Gary and Amy 1997), and to the relationships and ecosystems that span the firm's boundary (Dyer and Harbir 1998; Jacobides, Carmelo and Annabelle 2018). Beneath this theoretical pluralism lie two deeply held assumptions so that they are seldom stated. The diffusion of artificial intelligence (AI) and the empirical composition of the global economy now question both.

The first assumption is anthropocentric. The field's account of how advantage is created and renewed locates causal agency in human actors. These include the reasoned judgment of senior management (Andrews 1971), the tacit knowledge of individuals (Grant 1996; Nonaka 1994), the cognition and attention of decision-makers (Helfat and Margaret 2015; Ocasio 1997), and the situated practice of strategists (Vaara and Richard 2012; Whittington 1996). The premise in the micro foundations program, holds that organization-level constructs such as capabilities and routines cannot be explained without reference to individuals' actions and interactions (Felin, Nicolai and Robert 2015; Foss 2011). Yet AI systems increasingly perform the forecasting, analysis, and evaluative tasks that were formerly done by humans, and in doing so enter the coordination and decision processes through which strategy is enacted (Csaszar and Tom 2022; Krakowski, Johannes and Sebastian 2023; Krogh 2018). When consequential strategic action is distributed across human and algorithmic agents, the premise that macro-level strategy reduces to human action requires reconsideration.

The second assumption is contextual. The dominant paradigms were developed, tested, and refined on the experience of large firms in advanced economies, presupposing that economy's institutional infrastructure. These included reasonably efficient factor markets, enforceable property rights, deep pools of specialized talent, and reliable information intermediaries. In emerging and developing economies these conditions frequently do not hold. Where market-supporting institutions are missing or underdeveloped the condition of (Khanna and Krishna 2010) term institutional voids the nature and durability of advantage change (Hoskisson and Lorraine et al. 2000; Peng and Sunny et al. 2009; Wright and Igor et al. 2005). The scope conditions of the field's paradigms under institutional constraint are therefore not incidental. They rather bear directly on the settings in which most of the world's firms operate.

The two assumptions fail together, and most consequentially, at the point where they are least studied: the adoption of AI by firms in resource-constrained economies. There, the sources of advantage relocate toward data, prediction, and human-machine orchestration precisely where the data infrastructure, complementary capabilities, and institutional supports that convert those elements into advantage are least developed. Existing theory offers limited purchase on this intersection. The most direct precedent (Krakowski, Johannes and Sebastian 2023) analysis of how AI changes the sources of competitive advantage establishes the relocation of advantage toward data and complementary capabilities but, in common with the broader strategic analysis of AI, theorizes it for the institutionally rich settings of advanced economies (Agrawal, Joshua and Avi 2018; Gregory and Ola et al. 2021; Raisch and Sebastian 2021); it does not ask how that relocation is conditioned where the institutions that supply those complements are themselves absent. The converse literature, on emerging-economy strategy, engages only sparingly with the algorithmic transformation of the firm. The institutional contingency of algorithmic advantage falls in the gap between them.

This paper addresses that gap. Its contribution is not to restate that AI relocates advantage toward complements, nor merely to append an institutional caveat to that claim. It is to specify how the diffusion of algorithmic prediction alters the scarcity structure that underpins advantage, and to theorize the institutional environment as a set of link-specific moderators that determine whether firms can accumulate and appropriate the complements on which advantage now depends. Where (Krakowski, Johannes and Sebastian 2023) identify the destination of advantage under AI, this paper specifies the mechanism of its relocation and the conditions that govern arrival. It thereby integrates four literatures the resource-based and dynamic-capabilities traditions, the economics of AI, research on human-AI complementarity, and the institution-based view into a single explanatory framework, and it treats the resource-constrained economy not as a special case to be noted and set aside but as a theoretically informative setting in which the mechanisms linking algorithmic resources to advantage become unusually legible.

The paper pursues three objectives. First, it synthesizes the theory of competitive advantage to expose the anthropocentric and advanced-economy assumptions that the algorithmic and institutional frontiers unsettle. Second, it recognizes the sources of advantage for the algorithmic firm, arguing that AI commoditizes generic prediction and relocates advantage to strategically embedded data assets, managerial judgment, and the orchestration of human and algorithmic agents. Third, and centrally, it theorizes the institutional and infrastructural conditions of resource-constrained economies as boundary conditions that moderate, link by link, the translation of algorithmic resources into durable advantage, consolidating the argument into an integrative framework and seven testable propositions. The overarching research question is therefore: how must the dominant paradigms of competitive advantage be reconceived when strategic action is distributed across human and algorithmic agents operating under the institutional and infrastructural constraints of resource-constrained economies?

The remainder of the paper proceeds as follows. Section 2 states the review's approach and scope. Section 3 offers a compressed synthesis of the theory of competitive advantage and positions the paper's contribution against it. Section 4 recognizes the sources of advantage under AI. Section 5 defines the resource-constrained institutional environment and develops its link-specific moderation of the pathway to advantage. Section 6 integrates the argument into a framework, advances the propositions and their boundary conditions, and states the theoretical contributions. Section 7 sets out a research agenda, and Section 8 concludes.

2. Review Approach and Scope

This study is an integrative conceptual review being methodological rather than merely terminological in nature. Current research synthesizes theoretically distinct research streams developing new conceptual structure to reconceive what the sources of competitive advantage are, and how they are to be understood, for the algorithmic firm under institutional constraint. Hence integrative review, which interprets and connects bodies of work in order to build theory, is the fitting method (Snyder 2019; Torraco 2005).

The review synthesizes four research streams. The first is the theory of competitive advantage, which supplies the analytical machinery resource heterogeneity, imperfect imitability, complementary assets, and dynamic reconfiguration through which advantage has conventionally been explained (Barney 1991; Teece, Pisano, and Shuen 1997). The second is the economics of AI as a

prediction technology (Agrawal, Joshua Gans, and Avi 2018, 2019) together with the theory of data network effects (Gregory and Ola et al. 2021). The third is the organizational and paradox-theoretic analysis of human–machine collaboration (Krakowski, Johannes and Sebastian 2023; Raisch and Kateryna 2025; Raisch and Sebastian 2021). The fourth is research on strategy in emerging and developing economies, from which the review draws the institution-based view and the concept of institutional voids (Hoskisson and Lorraine et al. 2000; Khanna and Krishna 2010; North 1990; Peng, Denis and Yi 2008; Peng and Sunny et al. 2009; Wright and Igor et al. 2005). The contribution lies in the disciplined integration of literatures that are ordinarily pursued in isolation.

Consistent with this orientation, the corpus was assembled purposely rather than exhaustively, following a transparent selection logic. Foundational sources were identified from the canonical contributions that established or decisively reoriented each stream, traced through the citation networks of authoritative reviews of the strategic-management field (Furrer, Howard and Anna 2008; Hoskisson and William et al. 1999; Mintzberg, Bruce and J. Lampel 1998; Ronda-Pupo and , and Luis 2012). These were supplemented with recent conceptual and empirical work at the algorithmic and institutional frontiers, located through targeted searches of leading management and strategy outlets for the period 2018–2025 using combinations of terms including artificial intelligence, machine learning, prediction, data network effects, human–AI collaboration, competitive advantage, dynamic capabilities, institutional voids, and emerging economies. Sources were included when they either supplied theoretical machinery central to one of the four streams or documented the current state of debate at their intersection, and were excluded when they treated AI at a purely technical level without organizational or strategic implication, or addressed competitive advantage without bearing on the algorithmic or institutional questions at issue. The theory of competitive advantage is treated in compressed form in Section 3 at the level of detail required to expose the assumptions the subsequent analysis engages, rather than surveyed for its own sake and readers seeking comprehensive genealogies of the field are well served by existing narrative and bibliometric treatments (Furrer, Howard and Anna 2008; Ronda-Pupo and Luis 2012). Transparency here consists not in the reproduction of a search string but in the explicit statement of the selection logic and scope, which readers can inspect and contest.

Two limitations follow from this design and are stated at the outset. First, purposive selection is inherently interpretive: another reviewer might weight contributions differently or draw the boundaries of the frontiers more widely or narrowly. Second, the paper's claims are conceptual propositions formulated for empirical test, not findings established by it. A valuable extension would triangulate the interpretive synthesis offered here against a systematic bibliometric mapping of the AI-and-strategy literature and against primary evidence from technology-adopting firms in developing economies; both lie beyond the present scope and are identified as priorities in Section 7.

3. Theoretical Foundations: The Sources and Scope Conditions of Competitive Advantage

3.1 Competitive Advantage and Its Machinery

The organizing construct for strategic management was competitive advantage. The competitive advantage of a firm is the strategy it follows that creates value for the firm that is not followed by any other firm; the competitive advantage of a firm is sustained when competitors cannot replicate the value creating strategy of the firm (Barney 1991). This formulation turned the focus of the field from the outcome of the performance to the circumstances of its resistance to competitive erosion, and made imitation and substitution the analytical axis for the theory.

The two bedrock responses to the field placed the origins of advantage in different areas. The positioning approach was heavily influenced by industrial-organization economics and positioned the sources of profitability in the industry structure, and strategy was defined as the positioning against the competitive forces (Porter 1980, 1985). The resource based view (RBV) shifted the analysis to the inside, focusing on the advantages that a firm could gain from the heterogeneous resources it has accumulated and controlled (Penrose 1959; Wernerfelt 1984) and on the conditions under which a resource can be a source of sustained advantage: It should be valuable, rare, imperfectly imitable and non-substitutable; the unique history and causal ambiguity related to the resource and social complexity are the key conditions that make it imperfectly imitable (Barney 1991; Peteraf 1993). Complementary contributions established that competitively valuable resources are frequently non-tradable and must be accumulated internally over time (Dierickx and Karel 1989), and that their value in strategic factor markets depends on managerial expectations (Barney 1986).

Two features of this machinery are essential to the argument that follows. First, advantage rests not on resources in isolation but on their combination with complementary capabilities that render them productive and difficult to replicate: possession is not appropriation (Sirmon and Michael et al. 2011). Second, the RBV explains the possession of advantage more convincingly than its creation and renewal a limitation acknowledged by sympathetic assessments (Barney, Mike and David 2001; Kraaijenbrink, C. Spender, and Aard 2010) and one that exposed the theory to the charge of tautology, since valuable resources are partly identified by the advantage they are invoked to explain (Priem and John 2001).

3.2 Dynamic Capabilities and Reconfiguration

Two extensions addressed the RBV's static character. The knowledge-based view treated knowledge particularly tacit, difficult-to-imitate knowledge as the resource of pre-eminent strategic significance and the firm as an institution specialized in its integration and creation (Grant 1996; Nonaka 1994), with the capacity to absorb and apply external knowledge itself path-dependent and cumulative (Cohen and Daniel 1990). More consequentially, the dynamic-capabilities perspective introduced a higher-order construct the firm's capacity to integrate, build, and reconfigure competences to address rapidly changing environments (Teece, Gary and Amy 1997) subsequently disaggregated into sensing opportunities and threats, seizing them through resource mobilization and business-model design, and reconfiguring assets to maintain fitness (Teece 2007). On this account the business model is the mechanism that converts capability into appropriate value, a mechanism of heightened consequence where new technologies unsettle established models of value creation and capture (Teece 2010).

The perspective's influence has been accompanied by unresolved contention. A consequential reformulation held that dynamic capabilities often resemble identifiable best-practice routines whose value is contingent on market dynamism, implying that the source of sustained advantage recedes to the resource configurations they produce rather than the capabilities themselves (Eisenhardt

and Jeffry 2000). The construct has also drawn charges of definitional circularity, infinite regress, and ontological ambiguity dynamic capabilities are variously processes, routines, decisions, or emergent properties difficulties mitigated only in part by distinguishing the exercise of a capability from its underlying nature and ordinary from dynamic capabilities (Helfat and Margaret 2003; Teece 2014). The perspective remains the field's principal response to advantage under conditions of change and continues to evolve at the nexus of strategy, international business, and digitalization (Pitelis, David and Hongyi 2024).

3.3 Advantage beyond the Firm's Boundary

The two paradigms, resource-based and knowledge/ability-based, have the same underlying assumption: The firm is the container of the advantage. This is relaxed by a parallel theory. The relational view suggests that critical assets can be shared between the firms rather than being within the firms themselves and thus can create co-created rents that are not appropriate by any single firm (Dyer and Harbir 1998). Ecosystem theory also gains from the relationships of actors that work together in non-hierarchical ways around a value proposition, rather than through hierarchy or generic complementarities (Adner 2017; Jacobides, Carmelo and Annabella 2018). These views rethink advantage as a spectrum between industry and firm and onto the network, and emphasize problems of appropriability and governance, problems that are heightened at the digital frontier where platforms and data complementarities play a major role in the competition.

3.4 Micro Foundations and Two Latent Assumptions

The micro foundations program cuts across these paradigms, treating organization-level explanations as incomplete unless grounded in individuals' actions and interactions, and macro-to-macro relationships as typically mediated by micro-level processes (Felin, Nicolai and Robert 2015; Foss 2011). Applied to strategy, it foregrounds the cognitive and behavioral dimensions of capability: the theory of dynamic managerial capabilities built on managerial cognition, human capital, and social capital (Adner and Constance 2003; Helfat and Jeffery 2015), and its connection to the attention-based view of how the limited attention of decision-makers is allocated within the organization (Ocasio 1997).

This synthesis exposes two assumptions that organize the field without being argued for. The first is anthropocentric: across the positioning, resource, knowledge, capability, and practice traditions, and most explicitly in the micro foundations program, the ultimate bearer of strategic agency is a human actor. The second is contextual: the machinery of advantage factor markets in which resources are priced and traded, the internal accumulation of non-tradable assets, and the appropriation of rents through enforceable contracts and property rights presupposes the institutional infrastructure of advanced economies. Neither assumption is mistaken; each is a scope condition that has gone unnamed. Table 1 summarizes the principal paradigms along common dimensions, and Table 2 previews how the framework developed in Sections 4–6 extends each. The two sections that follow examine what becomes of the theory of advantage when each unnamed condition is relaxed first by the entry of algorithmic agents, then by the institutional realities of resource-constrained economies.

Table 1: Principal paradigms of competitive advantage and their unnamed scope conditions

Paradigm	Locus of advantage	Representative works	Principal limitation / unnamed scope condition
Positioning (IO economics)	Industry structure and defensible market position	Porter (1980, 1985)	External orientation; static, equilibrium logic
Resource-based view	Valuable, rare, inimitable, non-substitutable resources	Wernerfelt (1984); Barney (1991); Peteraf (1993)	Static; risk of tautology; under-specifies value creation
Knowledge-based view	Integration and creation of tacit knowledge	Nonaka (1994); Grant (1996)	Underspecifies deliberate renewal of the knowledge base
Dynamic capabilities	Higher-order capacity to reconfigure resources under change	Teece, Pisano, and Shuen (1997); Teece (2007)	Definitional ambiguity; regress and measurement problems
Relational and ecosystem views	Interfirm relationships and ecosystem alignment	Dyer and Singh (1998); Adner (2017); Jacobides, Cennamo, and Gawer (2018)	Appropriability and governance of joint rents; indeterminate boundaries
Process, practice, micro-foundations	Situated praxis and individual-level mechanisms	Mintzberg and Waters (1985); Felin, Foss, and Ployhart (2015)	Weak link to performance; the problem of emergence

Because the paper builds directly on established theory, the precise nature of its contribution is best stated by specifying what it takes from, and adds to, each perspective it integrates. Table 2 makes that positioning explicit: for each perspective it identifies what the perspective explains, what it leaves unspecified in the algorithmic and institutional context, and what the present framework adds. The remainder of the paper develops each of these additions in turn.

Table 2: Positioning the framework: what it extends in, and adds to, each perspective it integrates

Perspective	What it explains	What it leaves unspecified for the algorithmic firm under constraint	What this framework adds
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Resource-based view	Resource heterogeneity and imperfect imitability as sources of advantage	Why AI renders generic predictive capability rapidly commoditized	Specifies the relocation of advantage from models to strategically embedded data assets and complementary-capability bundles
Dynamic capabilities	Reconfiguration of competences under technological change	Agency when reconfiguration is performed jointly by human and algorithmic agents	Defines human–AI orchestration as a hybrid, higher-order capability and operationalizes it
Economics of AI / AI and competitive advantage	Prediction as the locus of value; data and complementarity	Institutional contingency; the analysis is set in institutionally rich contexts	Introduces link-specific institutional moderation of the AI-to-advantage pathway
Institution-based view	Institutional conditions as determinants of strategy and performance	The place of algorithmic resources and the specific links institutions govern	Shows precisely where institutions enter the pathway from algorithmic resources to appropriated advantage
Microfoundations	Capability as grounded in human action and interaction	Algorithmic agents as co-constituents of strategic action	Respecifies micro foundations around human–algorithm interaction

4. From Algorithmic Access to Algorithmic Advantage

This section consolidates the strategic analysis of AI into an account of how the sources of advantage are relocated, extending (Krakowski, Johannes and Sebastian 2023) argument that AI changes those sources. The synthesis is not itself the paper's central novelty; it is the platform for the contribution advanced in Sections 5 and 6 that the relocation described here is systematically conditioned by the institutional environment, such that its character in resource-constrained economies is not a special case but a revealing one.

4.1 Artificial Intelligence as Prediction and the Relocation of Value

The most analytically tractable account of contemporary AI treats it as a technology that lowers the cost of prediction the generation of information about unknown states from known data (Agrawal, Joshua and Avi 2018).

The easy interpretation of this is obvious: the more affordable predictions become, the greater the value of their complements. A prediction does not equal a decision. It is only relevant in the context of judgment regarding payoffs and actions (Agrawal, Joshua and Avi 2019), and judgment isn't simply an afterthought downstream but a limitation on what prediction can achieve. In situations where 'strategic problems' can be expressed as a measurable risk; superior prediction is crucial; in situations where 'strategic problems' can only be expressed as a 'genuine uncertainty' the identification of which futures are even representable is a distinctly human contribution that superior prediction cannot provide (Townsend and Richard et al. 2025). The strategic implications are that the returns to AI are divided in three: a predictive return to the data that is used for prediction, a judgmental return to the judgment that takes prediction and translates it into action, and an organizational return to the integration of prediction with judgment.

This relocation is a consequence of the machinery in Section 3. The more widely adopted predictive techniques and tooling become, the more common and easier to duplicate the capability to build and run models through generally available methods. It is precisely this generic capability that fails the imperfect-imitability condition; what does not fail is the proprietary data on which prediction draws and the organizational apparatus that turns prediction into decision. Advantage therefore cannot reside in prediction as such. It resides in prediction's complements: proprietary data assets accumulated over time, judgment encoded in decision architectures, and the capability that orchestrates prediction within the organization. The analytical center of gravity shifts from the algorithm to the complements, an implication the resource-based tradition anticipates but, in its classical form, does not theorize for algorithmic resources.

Precision on this point requires distinguishing two capabilities that the term prediction conflates. Generic predictive capability: the capacity to apply standard techniques to standard problems is increasingly accessible, imitable, and commoditized, and confers no durable advantage. Context-specific predictive capability: the capacity to convert proprietary data into predictions that are embedded in the firm's workflows, tuned to its decisions, and integrated with the judgment of its managers is a different construct: it is causally ambiguous, socially complex, and potentially difficult to imitate. The seeming contradiction, that is, the loss of the prediction-based edge, and the maintenance of it, simply falls apart once the two are split apart. The generalizable aspect of prediction is a diffused one, the institutionalized aspect of prediction into decision is defensible. This is not about predicting better in abstract, but about integrating the prediction more and more into an organization that can't be easily recreated by the competition.

4.2 Strategically Embedded Data Assets

Data is often spoken of as a "strategic asset" of the algorithmic company, but here, "strategic asset" needs to be qualified, as not all data is strategically valuable. Data meets the value and rarity requirement for the RBV and may be difficult to imitate through time compression and through privileged access (Dierickx and Karel 1989) but only under certain circumstances. It is task specific and not generic: a dataset that may be useful for one predictive task may not be useful for another. It only makes sense when the raw data is translated into actionable predictions, via complementary engineering, integration, and governance skills. Where these capabilities exist, value can compound as data builds up: Data network effects can help to drive an advantage as a system learns from its use, users provide more data, which then increases the value of the system for users, etc. (Gregory and Ola et al. 2021). Importantly, these effects are not inherent and are only amplified by the complementary organizational capabilities of legitimization, data stewardship, and user-centric design, not just data volume (Gregory and Ola et al. 2021).

These qualifications suggest that the key construct strategically relevant is not data, but the level of strategic embeddedness of a data asset. Raw data becomes structured data, structured data becomes a proprietary data, a proprietary data becomes a task-

specific data when tuned to a specific decision, a task-specific data becomes a continuously refreshed data when a feedback loop refills it, and a continuously refreshed data becomes an organizationally embedded when it is fused with the workflows, judgment, and governance that render its value causally ambiguous. At the highest level on this hierarchy, data is a source of sustainable competitive edge. The theoretical object, then, is best described as the causally ambiguous, socially complex, genericized bundle of data and the complementary capabilities which make it productive, which I call the "strategically embedded data asset. The relevant question is not "Does data give an edge?" but "When?" and the answer is the same as for isolated resources: They don't give one.

4.3 Human–AI Orchestration as a Hybrid Capability

When prediction is plentiful and judgment and integration are absent, the power to create advantage is the division of labor orchestration between man and machine. The automation and augmentation paradox is that this situation is not neatly split into automation and augmentation, but instead must be balanced (Raisch and Sebastian 2021). Algorithmic augmentation without human calibration and contextualization drops human judgment while algorithmic efficiency without human calibration and contextualization drops economic consequences of prediction. The paradox has been reinterpreted as a hybrid problem-solving problem, involving the autonomous and sequential modes of human-machine intelligence combination and their interactive modes, highlighting the need of configuration and not in any individual component (Raisch and Kateryna 2025).

This reframing takes the logic of dynamic capabilities down to the algorithmic level. Humans and algorithmic agents together are sensing, seizing, and reconfiguring by. Sensing is being done by algorithmic monitoring of markets and operations, seizing via redesigning business models around the capability of predicting, and reconfiguring via the reallocation of tasks, roles and decision rights among human and machines (Teece 2007; Warner and Maximilian 2019). The orchestrated division of labor does not stop with prediction, but encompasses evaluation too. Algorithmic systems can genuinely evaluate strategic tasks, and the aggregated algorithmic assessment can be a close approximation of expert human judgment despite variations in individual assessments (Doshi and J. Jason et al. 2025). What separates firms, however, is not whether they possess AI, but whether they can reorganize the firm around AI. It highlights that they can reorganize at the system level, not at the point solution level, and part of a larger digital transformation of the firm (Agrawal, Joshua and Avi 2022; Verhoef and Thijis et al. 2021; Volberda and Saeed et al. 2021). Orchestration capability is less amenable to emulation than are the algorithmic resources it coordinates due to its process-embedded, causally ambiguous and socially complex nature.

Orchestration capability needs to be operationally specified to be analytic traction and not simply a catch-all. It can be broken down into six component dimensions, namely, task allocation, i.e., how tasks are assigned to humans versus algorithmic agents; decision-right allocation, i.e., who has the final say or say; workflow integration, embedding prediction into workflow; exception handling, i.e., how humans intervene when algorithmic agents fail to perform; learning and reconfiguration, i.e., the ability to adapt the human-machine system based on experience; and governance, i.e., the management of error, bias, accountability, and data quality. These dimensions are outlined in Table 3, along with their strategic role. Orchestration in this form differentiates between high and low levels of orchestration capability, and it serves as an identification of the organizational competency that is lacking, and thus the orchestration competencies that are rate limiting for advantage in the resource-constrained environment.

Table 3: Dimensions of AI orchestration capability

Dimension	Definition	Strategic function
Task allocation	Deciding which tasks are performed by algorithms and which by humans	Aligns the comparative advantage of each agent with task characteristics
Decision-right allocation	Determining who or what holds final authority over a decision	Preserves accountability and calibrates reliance on prediction
Workflow integration	Embedding prediction into organizational routines and processes	Converts prediction into decision-relevant action at scale
Exception handling	Enabling human intervention when algorithms perform poorly or face novel conditions	Guards against automation failure under uncertainty
Learning and reconfiguration	Revising the human-machine system on the basis of experience	Sustains fitness as tasks, data, and conditions change
Governance	Monitoring error, bias, accountability, and data quality	Secures trust, legitimacy, and the integrity of the data-feedback loop

4. Hybrid Micro Foundations

The entry of algorithmic systems into coordination and decision processes is a theoretical challenge besides operational one. When a strategic actor is a hybrid human–algorithmic actor, the micro foundational premise that macro-level strategy reduces to human action and interaction requires re-specification (Csaszar and Tom 2022; Doshi and J. Jason et al. 2025; Krakowski, Johannes and Sebastian 2023; Krogh 2018). The individual-level processes through which capability is enacted managerial cognition, attention, and judgment (Helfat and Jeffery 2015; Ocasio 1997) do not disappear. They become co-constitutive with algorithmic inference. The explanatory locus shifts from managerial cognition alone to the interaction between managerial judgment and algorithmic prediction, and the micro foundations of capability must be re-specified at that interaction (Raisch and Kateryna 2025).

This specification is the micro-level account of the orchestration capability on which the argument turns. The chain runs from the institutional environment, which shapes the human and technical capital available to a firm, to the orchestration capability those interactions constitute, the decision quality it produces, and finally to competitive advantage. Orchestration capability, is the organization-level construct whose micro foundations are the patterned interactions of human and algorithmic agents; specifying those

micro foundations is what makes the capability theoretically coherent and its imitation barriers intelligible. The field's constructs capabilities, routines and advantages are retained; what changes is that the agents whose action explains them are now hybrid. A theory of the algorithmic firm accordingly requires an account of how strategic agency is distributed between humans and machines, their combination into a coherent capability, and resistance imitation by this capability.

4.5 The Transience of Prediction-Based Advantage

The final implication concerns durability. Advantage based on predicting accuracy is volatile, being washed away by common technique, common tooling and the movement of talent, consistent with the overall diagnosis that advantage in dynamic environments is fleeting and must be continually re-created (D'Aveni and Robert 1994; McGrath 2013). Durable advantage moves to where convergence doesn't eat away proprietary data-feedback loops that can't be replicated by others and causally ambiguous orchestration processes it to decision. This thinking puts the algorithmic company on the historical imbalance between creating and losing an advantage (Nelson and Sidney 1982) highlighting the importance of reconfiguring the system. The value to be gained from AI is not the algorithms and tools but the data and orchestration that are not subject to algorithms or tools.

5. Institutional Conditions of Algorithmic Advantage

5.1 Defining the Resource-Constrained Institutional Environment

Above analysis needs precision as the term resource-constrained economy is not synonymous with developing economy and is not homogeneous. It is a multi-dimensional institutional context where five conditions that enable the generation of advantage from algorithmic resources are relatively scarce or insecure. Firstly and secondly, the digital and data infrastructure in which AI resources are used, including connectivity, data and quality, and factor markets for specialized AI and managerial skills. Thirdly market-supporting intermediaries providing information, certification and trust while fourthly property-rights and contract-enforcement mechanisms that determine who has control over the data and returns. Lastly, complementary financial and organizational resources needed to build up the capability. These dimensions are defined by Table 4, with the pathway link that each one will be considered as primarily governing.

Three differences make the construct sharper. First, resource constraint is multidimensional, and not scalar. an economy producing exports yet lacking managerial expertise is constrained in other ways than one with low incomes and weak data systems or a transition economy with an idiosyncratic property rights regime. Second, resource constraint is not equivalent to low national income, to developing or emerging status, or to any categorical label; these correlate with, but do not define, the institutional conditions at issue. Third, institutional strength is a continuum that does not map neatly onto national income: advanced economies can exhibit specific voids in. Treating the construct as multidimensional and continuous avoids the twin errors of romanticizing institutional thickness in advanced economies and treating developing economies as uniformly deficient. The framework that follows specifies which dimensions bind, and through which links, rather than assigning economies a single degree of constraint.

Table 4: Dimensions of the resource-constrained institutional environment

Dimension of constraint	What is limited or unreliable	Pathway link principally moderated
Digital and data infrastructure	Connectivity; digitization, completeness, and quality of data	Data to prediction; the data-feedback loop
Factor markets for talent	Supply of data-engineering, machine-learning, and orchestration talent; retention against international mobility	Prediction to decision (accumulation of complements)
Market-supporting intermediaries	Information, certification, and trust intermediaries	Data availability to data quality and trust
Property rights and appropriability	Contract enforcement; secure control over data and returns	Decision to appropriated rent
Complementary financial and organizational resources	Capital and organizational slack for capability accumulation	Cross-cutting; conditions all links
Dimension of constraint	What is limited or unreliable	Pathway link principally moderated

5.2 Institutional Voids and the Institution-Based View

Above mentioned reconstructed theory (Section 3) assumes institutional frameworks that are not universal. Emerging and developing economies show that market-supporting institutions, information intermediaries, contract-enforcement mechanisms, property-rights regimes, and factor markets that allow transactions to proceed efficiently are frequently absent or weak, a condition termed as institutional voids (Khanna and Krishna 2010). Firm strategy and performance are governed by the rules of the game actually in force, which differ systematically from those assumed in the field's dominant paradigms (North 1990). This recognition is the institution-based view, which treats a firm's strategy and performance as shaped by its formal and informal institutional environment alongside industry conditions and firm resources (Peng, Wang, and Jiang 2008; Peng et al. 2009). Institutions are not a peripheral contingency but a fundamental determinant of advantage, omitted from theories developed in settings where their presence could be taken for granted (Hoskisson and Lorraine et al. 2000; Wright and Igor et al. 2005).

The institution-based view is the moderator the theory of the algorithmic firm requires. AI relocates advantage toward data, prediction, and orchestration (Section 4); whether that relocation issues in advantage depends on institutional conditions that govern access to data, the operation of markets for complementary capability, and the appropriation of returns. The algorithmic firm is an institutionally embedded firm, and its sources of advantage are institutionally contingent.

5.3 Link-Specific Institutional Moderation

The value of the institution-based view lies not in the general observation that institutions moderate advantage but in the specification of where they do so. The pathway from algorithmic resources to appropriated advantage comprises distinct links, and different institutional conditions gate different links. Stating the moderation link by link converts a general contingency into a set of testable relationships.

The first link runs from data to predictive capability, and it is gated by digital and data infrastructure and by information intermediaries. Where data is incompletely digitized, sparse, or of low quality, and where connectivity to shared data assets is limited, the raw material of prediction is scarce and unreliable, and the data-network effects that entrench advantage where data is abundant are correspondingly weak or absent (Gregory Ola et al. 2021). Weak certification and information intermediaries compound the problem by degrading the quality and trustworthiness of the data that is available.

The second link runs from prediction to decision of the conversion of predictive capability into decision-relevant action and it is gated by factor markets for specialized talent. The binding constraint at this link is typically not access to algorithms, which as general-purpose tools diffuse cheaply, but the availability of the complementary capabilities that convert data into decision-relevant prediction. Markets for data engineers, machine-learning specialists, and managers capable of orchestrating human-machine complementarity are thin, and such talent is internationally mobile, depleting local pools. The scarce and inimitable element is not the algorithm but these complementary capabilities, which must be accumulated over time within the organization and whose formation is impeded by voids in labor and education markets (Dierickx and Karel 1989).

The third link is from decision to appropriated rent, and it is gated by property-rights and appropriability regimes. Weak contract enforcement and insecure control over data and returns make it difficult to capture the value that algorithmic resources create. The net effect is a systematic re-weighting of the sources identified in Section 4. Predictive capability is no less accessible than elsewhere, while proprietary data becomes harder to accumulate and the orchestration and complementary capabilities become the decisive and binding factor.

5.4 Institutional Voids as Constraint and as Opportunity

Institutional voids are not only limitations, but also opportunities for gain. A firm that constructs the missing infrastructure can have the same effect on the pathway to advantage as a lack of it in the market. If there is no reliable data intermediary, no trusted digital platform or no proprietary identity and transaction data, a firm that provides these becomes a valuable asset. An institutional void has two sides. An institutional void constrains a firm that relies on that missing institution, while it also creates an opportunity for a firm that can provide the institution because the infrastructure the institution creates and the data the infrastructure generates is hard for a rival to replicate. This links the view of the institution to the view of the resources. Institutional gaps can be filled by firm, a path to the causally ambiguous, socially complex data assets that are the basis of sustainable advantage (Khanna and Krishna 2010; Wright and Igor et al. 2005).

For example, in export intensive manufacturing, particularly ready-made-garment industry, that within a company, they have access to AI tools, but the data engineering and managerial skills needed to de-risk and make them a decision advantage are not common and mobile globally. Under such circumstances, adoption will only provide short-term parity, not lasting advantage, because the limiting factor is the complements, not the tools. In consumer finance, the same institutional gaps are conducive to the establishment of the very institutions that have created the missing infrastructure. If formal credit-scoring intermediaries are missing, providers of mobile-money and digital-payment systems have created their own transaction and identity data and turned a void into an asset and a defensible position.

5.5 Democratization or Divergence? Reconciling the Debate

The argument takes place along the line between two accounts, which are in conflict, of the results of AI on economies of scarcity. As stated, each as a mechanism, and not as an optimistic or pessimistic attitude, will help clarify the content and compatibility of each with the existing structure.

The first is the account of democratization and leapfrogging. Modern AI models and tooling are general purpose and low-cost, and makes it easier for lower-income economy firms to adopt frontier capabilities than it would be for them to develop fixed-line telephony, and bypass stages of development. The current system goes with the premise but restricts the inference. It is not the models that are valuable for prediction. Their complements including proprietary data, integration or orchestration capabilities, and judgment (encoded in decision architectures), which are institutionally gated (Section 5.3), so the democratization of the tool does not imply the democratization of advantage. Leapfrogging is not precluded, but rather allowed by the framework (Proposition 7); it is possible where firms install the infrastructure that they do not have.

The second is the divergence account, which was pushed hardest by the economists: AI will be saving labor and resources, and will show “winner take all” dynamics, which will lead it to take the comparative advantages out of the low-cost labor on which developing economies have relied, focusing the gains in the advanced economies that hold the technology and the data (Korinek and Joseph 2021). This is an argument at the level of national comparative advantage, a higher level of aggregation than the firm-level analysis pursued here. The two are compatible, and indeed complementary: even as AI erodes a developing economy's factor-cost advantage, the question of which firms within it can build durable advantage remains a question of complementary capability. If anything, the divergence account raises the stakes of the firm-level analysis, because as factor-cost advantage diminishes, capability-based advantage becomes more, not less, decisive.

The apparent tension between the two accounts, and the objection that this framework both discounts and invokes infrastructure, dissolves once access and advantage are distinguished. The divergence literature documents widening cross-national gaps in AI adoption driven substantially by differences in data and compute infrastructure conditions this framework treats explicitly as moderators. The claim is not that infrastructure is irrelevant but that, given the diffusion of general-purpose models, the binding constraint on firm-level advantage is the institutionally gated complements rather than access to the models themselves. The cleaner statement of the paper's position is therefore that AI access can converge across economies while AI-enabled competitive advantage

remains heterogeneous. The framework developed in the next section aims to make these settings theoretically legible and empirically tractable, relocating the developing economy from the periphery of strategic theory to a site of its development.

6. An Integrative Theory of Algorithmic Competitive Advantage under Institutional Constraint

6.1 The Integrative Framework

To bring into focus the argument presented here, it is summarized within the integrative framework of three layers as shown in figure 1. The first layer includes algorithmic resources, general-purpose models, compute, digital infrastructure and proprietary, task-specific data. The second consists of the organizational change needed to turn those resources into decisions: prediction, judgment, human-AI orchestration, allocation of decision rights, and reconfiguration. The third is efficiency of competitive outcomes, innovation, differentiation and, if the pathway is finished, appropriated and defensible advantage. The benefit of being used is fed back into the data layer, resulting in a data-network effect as usage creates the data that enhances future prediction.

The institutional and infrastructural conditions of the firm's context data infrastructure, as well as the availability of factor markets for complementary talents, property-rights and appropriability regimes, and information intermediaries run vertically across all three layers. These conditions affect the force of each link. In institutionally thick environments, the pathway is open and it works at full force, while in resource-poor environments, certain connections tie together and the limiting factor becomes the complementary dynamics that transform the algorithmic resources into advantage. The framework's central claim is thus made visual: the sources of advantage for the algorithmic firm are not the algorithmic resources but the data and orchestration complement that resist imitation, and whose accumulation and appropriation are institutionally gated. It integrates the resource-based emphasis on inimitable complements (Barney 1991; Dierickx and Cool 1989), the dynamic-capabilities emphasis on reconfiguration (Teece 2007), the micro foundational premise respecified for hybrid agency (Section 4.4), and the institutional embeddedness of the firm (Peng and Sunny et al. 2009).

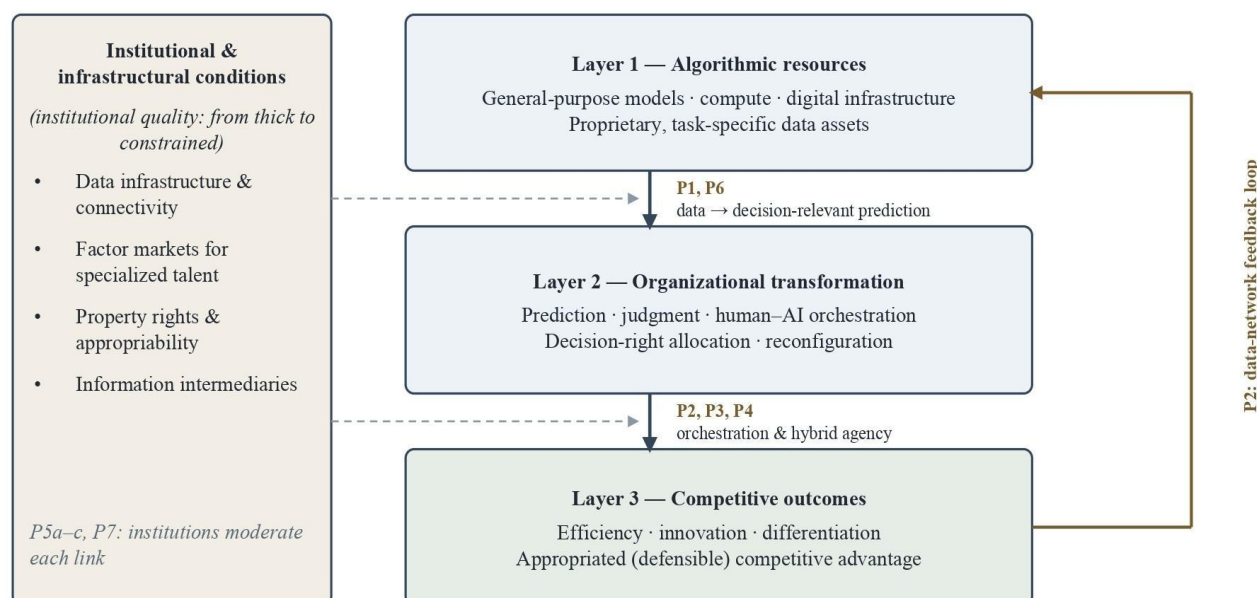


Figure 1: An integrative framework of algorithmic competitive advantage under institutional constraint. Algorithmic resources (Layer 1) are converted, through prediction, judgment, and the orchestration of human–machine complementarity (Layer 2), into competitive outcomes (Layer 3); the resulting advantage is causally ambiguous and socially complex (P1–P3). A feedback loop returns realized advantage to the data layer, capturing the data-network effect (P2). Institutional and infrastructural conditions cut vertically across the model and moderate each link—permissive in institutionally thick settings and binding in resource-constrained ones, where the decisive constraint shifts to the complementary capabilities that convert algorithmic resources into advantage (P5–P7).

6.2 Theoretical Mechanisms and Propositions

The relationships implied in the synthesis are stated in causal testable form in the following propositions. They are hypotheses about a research program, not facts. Some of these are based on relationships where there is empirical evidence, and some are theoretical inferences from the integration of the four streams, and all are about relationships that have not been explored in the settings for which they are written. This status is noted in Table 5, along with the theoretical basis for the proposition and the institutional condition in which it is manifested. Propositions 1–4 address the movement of advantage in the realm of AI, and are a consolidation of Section 4; Propositions 5–7 address institutional moderation and contribute to the paper's core argument.

The framework's central proposition is Proposition 6, and the remaining propositions are best read in relation to it. It acts as a chain: the diffusion of general-purpose models reduces the rarity of predictive capability; declining rarity erodes the appropriability of advantage based on models; the relative importance of prediction's complements rises accordingly; institutional conditions constrain the accumulation of those complements; and the complements therefore become the binding constraint on advantage, generating firm-level variation that access to models does not explain. Propositions 1–4 establish the first three steps the relocation of

advantage to complements; Proposition 5 establishes the fourth the institutional constraint on complements; and Proposition 7 specifies the condition under which a firm escapes the constraint by internalizing the missing institution. Proposition 6 is the point at which the algorithmic and institutional arguments meet.

Proposition 1: The relationship between a firm's access to algorithmic resources and its competitive advantage is positively moderated by its complementary organizational capability: algorithmic resources generate greater competitive value where the firm possesses stronger data-integration and orchestration capabilities. The competitive value of algorithmic resources therefore derives less from the possession of data or models per se than from the capacity to convert data into decision-relevant prediction, and proprietary data confers durable advantage only in combination with complementary capabilities that rivals cannot readily assemble.

Proposition 2: As predictive models and techniques diffuse and converge across competitors, advantage grounded in prediction accuracy erodes toward transience; durable advantage relocates to proprietary data-feedback loops and to the causally ambiguous, socially complex orchestration processes through which prediction is integrated into decision. The rate of erosion is increasing in the diffusion of general-purpose models and decreasing in the strength of a firm's proprietary data-feedback loops.

Proposition 3: Where algorithmic systems perform sensing, analytic, and evaluative tasks, the higher-order capability that generates advantage is the orchestration of human–machine complementarity—the reconfiguration of tasks, roles, and decision rights across human and algorithmic agents—rather than automation or augmentation pursued in isolation. Competitive advantage is increasing in orchestration capability, specified across its constituent dimensions (Table 3).

Proposition 4: Where consequential strategic action is distributed across human and algorithmic agents, the micro foundations of capability require re-specification at the level of the human–algorithm interaction: the explanatory locus of orchestration capability shifts from managerial cognition alone to the interaction between managerial judgment and algorithmic inference, and the quality of that interaction mediates the relationship between algorithmic resources and competitive advantage.

Proposition 5: The translation of algorithmic resources into competitive advantage is moderated by the institutional and infrastructural conditions of the firm's context, and the moderation is link-specific. (a) Data-infrastructure voids incomplete digitization, fragmented or low-quality data, and limited connectivity weaken the link from data to predictive capability and suppress the data-feedback loops through which advantage is entrenched. (b) Factor-market voids in labor and education thin markets for data-engineering and orchestration talent, compounded by international mobility that depletes local pools weaken the link from prediction to decision by constraining the accumulation of complementary capability. (c) Property-rights and appropriability voids weak contract enforcement and insecure control over data and returns weaken the link from decision to appropriated rent.

Proposition 6 (central proposition): Because general-purpose models and tooling diffuse cheaply while their complements are institutionally gated, the binding constraint on algorithmic advantage in resource-constrained economies is the availability of complementary capabilities rather than access to algorithms. Access to models is therefore a weaker predictor of realized advantage in resource-constrained than in institutionally thick settings, and the causal contribution of complementary capabilities to advantage is correspondingly more observable in the former.

Proposition 7: Where a firm builds the market-supporting infrastructure that its environment lacks reliable data intermediaries, trusted digital platforms, or proprietary identity and transaction data it converts institutional voids into a source of advantage, partially offsetting the attenuation specified in Proposition 5. The durability of such void-filling advantage is increasing in the difficulty rivals face in replicating the infrastructure and the data it generates.

Taken together, the propositions reorient the analysis of advantage in algorithm-intensive contexts away from the algorithm and toward the institutionally gated complements, and they yield predictions about which firms build durable advantage when low-cost models meet scarce complements that neither the democratization nor the divergence account, taken alone, generates. They also imply that the role of complements is most clearly identified in resource-constrained settings, where their scarcity renders their causal contribution legible.

Table 5: Propositions: statement, evidentiary status, theoretical basis, and institutional moderation

Proposition (abbreviated)	Evidentiary status	Theoretical basis	Institutional moderation in resource-constrained economies
P1. Advantage rests on the capacity to convert data into decision-relevant prediction, not on data or models per se	Theoretical inference; supporting evidence on complementarity	RBV complements; economics of AI (Barney 1991; Agrawal, Gans, and Goldfarb 2018)	Thin factor markets for integration capability raise the scarcity of complements
P2. Prediction-based advantage erodes toward transience; durable advantage relocates to data-feedback loops and orchestration	Theoretical inference; consistent with transient-advantage evidence	Imperfect imitability; transient advantage (Dierickx and Cool 1989; McGrath 2013)	Weak data infrastructure limits feedback loops, accelerating erosion
P3. The decisive capability is the orchestration of human–machine complementarity	Theoretical inference; emerging evidence on hybrid problem-solving	Dynamic capabilities; automation–augmentation; hybrid problem-solving (Teece 2007; Raisch and Krakowski 2021; Raisch and Fomina 2025)	Scarcity of orchestration talent makes this capability the binding constraint

P4. Micro foundations require re-specification at the human–algorithm interaction	Theoretical inference (conceptual)	Micro foundations; organizational theory of AI (Felin, Foss, and Ployhart 2015; Csaszar and Steinberger 2022)	Uneven managerial and technical capital shapes how hybrid agency is enacted
P5. The data-to-advantage pathway is moderated link by link (a–c)	Theoretical inference from IBV; empirically testable	Institution-based view; institutional voids (Peng et al. 2009; Khanna and Palepu 2010)	Data-infrastructure, factor-market, and appropriability voids attenuate specific links
P6 (central). The binding constraint shifts from algorithmic access to complementary capabilities	Central theoretical claim; directly testable	Factor markets; general-purpose-technology diffusion (Dierickx and Cool 1989; Agrawal, Gans, and Goldfarb 2018)	Institutional voids in labor and education markets, not model access, bind advantage
P7. Void-filling converts institutional deficits into advantage	Theoretical inference; illustrated by consumer-finance cases	Institutional voids as opportunity (Khanna and Palepu 2010; Wright et al. 2005)	Weak market intermediaries create space to build proprietary infrastructure and data

6.3 Boundary Conditions

A theory is strengthened by specifying where it does not apply. The framework's explanatory power is greatest where AI has strategic relevance, where proprietary data is a plausible source of differentiation, and where advantage depends on the conversion of prediction into decision. Accordingly, its range is limited to the conditions given in Table 6. When the strategic importance of AI in a given industry is low, when data is not or only partially owned by the company, or when it is simply a matter of choosing a third party to provide an industry standard AI service, the shift of competitive advantage to data and orchestration is reduced and the propositions of the framework become less binding. The institutional argument is bound on two specific points. If models and compute are still very expensive or scarce, access may bind, making Proposition 6 appropriate; and, if institutional quality is high even with a lower national income, the moderation specified in Proposition 5 is correspondingly relaxed. The declaration of such boundaries protects against over-extensions of the framework, and clarifies conditions under which alternative explanations, either based on access or based on factor-cost, continue to hold.

Table 6: Boundary conditions of the framework

Boundary condition	Effect on the framework
AI has low strategic relevance to the industry	Relocation of advantage to data and orchestration complements is weak; positioning or physical-asset logics dominate
The firm lacks meaningful proprietary data	Strategically embedded data assets cannot form; P1 and P2 weaken
Advantage rests primarily on physical assets or regulatory position	Algorithmic complements are secondary; the framework is peripheral
The firm relies on standardized third-party AI services	Orchestration and data complements are limited; advantage is transient by construction
Models or compute remain genuinely scarce or costly	Access, not complements, may bind; this qualifies Proposition 6
Institutional quality is high despite low national income	Institutional moderation (Proposition 5) is relaxed; access and firm capability dominate

6.4 Theoretical Contributions

The framework makes three theoretical contributions, each addressed to a literature it integrates.

First, it contributes to the theory of competitive advantage by respecifying the scarcity structure on which advantage rests in the algorithmic firm. Classical resource-based theory identifies valuable, rare, and inimitable resources as a source of advantage. The framework helps identify how the availability of AI changes the nature of the scarce resource, making predictive power more commonplace and easier to mimic, while adding strategic value to complementary assets, such as strategically positioned data assets, judgment embedded in decision architectures, and orchestration capability. It thus shifts the focus from algorithmic resources to the ways in which they are turned into defensible advantages, and it draws a key distinction between general and specific prediction which dissipates the apparent paradox of algorithmic tools as enabling and undermining advantage.

Second, it is part of the micro foundations program that moves the locus of explanation from human action to human–algorithm interaction. Where the program grounds organization-level constructs in the actions and interactions of individuals, the framework extends the grounding to hybrid actors, treating orchestration capability as an organization-level construct whose micro foundations are the patterned interactions of human and algorithmic agents. Competitive advantage, on this account, increasingly emerges through human–algorithm interaction rather than through human action alone.

Third, it contributes to the institution-based view by showing that institutions do not merely influence the adoption of AI but determine how effectively algorithmic resources are converted into organizational capability and appropriated advantage. By specifying institutional moderation link by link, the framework converts a general contingency into a set of testable relationships; and by developing the two-sided role of institutional voids as constraint and as opportunity it identifies conditions under which institutional gaps become, for the firm that fills them, a source of capability rather than only a limit on it.

Jointly, these contributions treat the resource-constrained economy not as a disadvantaged setting to which existing theory is applied but as a theoretically informative setting in which the mechanisms linking algorithmic resources to advantage are identified with unusual clarity, because the complements on which advantage depends are scarce there and their causal contribution is therefore legible.

7. A Research Agenda

The framework and propositions translate into a research agenda organized around three priorities, summarized in Table 7.

The first priority is conceptual: the micro foundations of hybrid strategic agency. Specifying capability at the human–algorithm interaction (Proposition 4) requires a theory of how managerial judgment and algorithmic inference combine into coherent capability and protection of this combination from imitation. This work connects the micro foundations program (Felin, Nicolai and Robert 2015) to the organizational theory of AI and to emerging accounts of hybrid problem-solving (Csaszar and Tom 2022; Raisch and Kateryna 2025), and is largely undone.

The second priority is empirical and methodological, i.e., to test the propositions in the settings for which they are formulated. This requires primary evidence from technology-adopting firms in resource-constrained economies on how such firms accumulate data, build complementary capability, and orchestrate human–machine complementarity under constraint. It also concerns whether these complements, rather than algorithmic access, distinguish firms that achieve durable advantage. Such evidence would also adjudicate the democratization and divergence accounts at the firm level, by testing whether, holding model access constant, complementary capability separates firms achieving durable advantage from those achieving only transient parity (Proposition 6). Longitudinal and configurational designs are well suited to constructs defined by process and combination rather than by discrete effects (Eisenhardt and Jeffery 2000) and would help address the field's persistent difficulty in specifying causal mechanisms independently of the outcomes they explain.

The third priority is integrative, i.e., to establish the scope conditions of the dominant paradigms rather than presuming their universality. The institution-based view supplies the apparatus (Peng and Sunny et al. 2009; Wright and Igor et al. 2005). It aims to specify, for each source of algorithmic advantage and each link in the pathway, how the strength of the relationship varies with data-infrastructure, factor-market, and appropriability conditions (Proposition 5), thereby converting the developing economy from a setting in which theory is applied into one in which it is developed and tested.

Two cross-cutting extensions warrant note. A systematic bibliometric mapping of the AI-and-strategy literature would complement the interpretive synthesis offered and discipline claims about the field's trajectory (Furrer, Howard and Anna 2008; Ronda-Pupo and Luis 2012). The sustainability frontier, the reorientation of strategy toward stakeholder value and societal grand challenges (Bansal and H. C. Song 2017; Freeman and John 1984; George and Jennifer et al. 2016; Hart 1995; Porter and Mark 2011) intersects the agenda where algorithmic capability is directed toward resource efficiency and systemic outcomes in developing economies, an intersection this paper brackets but does not dismiss.

Table 7. A research agenda for algorithmic competitive advantage under institutional constraint

Research priority	Illustrative research questions	Suggested theoretical leverage
Micro foundations of hybrid agency	How do managerial judgment and algorithmic inference combine into coherent capability, and when is the combination inimitable?	Micro foundations; organizational theory of AI
Testing the propositions under constraint	Do complementary capabilities, rather than algorithmic access, distinguish firms achieving durable advantage in developing economies?	Dynamic capabilities; longitudinal and configurational methods
Institutional scope conditions	How does the strength of each link in the data-to-advantage pathway vary with data infrastructure, factor markets, and appropriability regimes?	Institution-based view; comparative, context-sensitive research
Data as an institutionally embedded resource	Under what conditions do data-feedback loops emerge where digital infrastructure is thin?	Data network effects; resource-accumulation theory
Algorithmic capability and systemic value	How is algorithmic capability directed toward resource efficiency and grand-challenge outcomes in developing economies?	Stakeholder theory; natural-resource-based view

8. Conclusion

Competitive advantage theory rests on two assumptions that the diffusion of AI and the composition of the global economy increasingly render untenable, that strategic agency is human, and that firms operate within the institutional infrastructure of advanced economies. Current study argues that the two assumptions fail together, and most consequentially at their intersection the adoption of AI by firms in resource-constrained economies and it has developed a conceptual account of what the theory of advantage becomes when both are relaxed.

The argument reframes the sources of advantage for the algorithmic firm. As AI lowers the cost of prediction, advantage migrates from generic predictive capability, which diffuses and converges, to the complements that resist imitation. These include strategically embedded data assets, proprietary data-feedback loops, and the causally ambiguous orchestration of human–machine complementarity. Whether these complements can be assembled and appropriated is institutionally determined. The resource-constrained context is therefore not a peripheral special case but a theoretically informative setting. Because the complements on which

advantage depends are scarce there, their causal contribution is more readily identified than in the data-rich, institutionally thick settings where abundance obscures it. This position locates the developing economy against both the expectation that cheap AI will equalize advantage and the expectation that it must inevitably widen the gap, placing the determinants of firm-level advantage in capabilities that are neither automatically available nor irretrievably foreclosed.

In developing economies, this reframing offers not an application of the field's dominant paradigms but an occasion to extend and test them. The propositions advanced here are a point of departure for that work. The theory of competitive advantage was built, over six decades, on the experience of a particular kind of firm in a particular kind of economy. Its next phase will be shaped by the firms and economies it did not originally have in view.

References

- Adner, Ron. 2017. Ecosystem as Structure: An Actionable Construct for Strategy. *Journal of Management* 43: 39–58. <https://doi.org/10.1177/0149206316678451>
- Adner, Ron, and Constance E. Helfat. 2003. Corporate Effects and Dynamic Managerial Capabilities. *Strategic Management Journal* 24: 1011–1025. <https://doi.org/10.1002/smj.331>
- Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2018. Prediction Machines: The Simple Economics of Artificial Intelligence. *Harvard Business Review Press*. <https://store.hbr.org/product/prediction-machines-updated-and-expanded-the-simple-economics-of-artificial-intelligence/10598>
- Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2019. Exploring the Impact of Artificial Intelligence: Prediction versus Judgment. *Information Economics and Policy* 47: 1–6. <https://doi.org/10.1016/j.infoecopol.2019.05.001>
- Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2022. Power and Prediction: The Disruptive Economics of Artificial Intelligence. *Harvard Business Review Press*. <https://store.hbr.org/product/power-and-prediction-the-disruptive-economics-of-artificial-intelligence/10580>
- Andrews, Kenneth R. 1971. The Concept of Corporate Strategy. *Third Edition*, Harvard University. <https://www.semanticscholar.org/paper/The-Concept-of-Corporate-Strategy-Andrews/e2f06e617f02fa11ffc031b451dd35c3a7b0b8cb>
- Ansoff, H. Igor. 1965. Corporate Strategy: An Analytic Approach to Business Policy for Growth and Expansion. *McGraw-Hill*. <https://archive.org/details/corporatestrateg0000anso/page/n5/mode/2up>
- Bansal, P., and H.-C. Song. 2017. Similar but Not the Same: Differentiating Corporate Sustainability from Corporate Responsibility. *Academy of Management Annals* 11: 105–149. <https://doi.org/10.5465/annals.2015.0095>
- Barney, Jay B. 1986. Strategic Factor Markets: Expectations, Luck, and Business Strategy. *Management Science* 32: 1231–1241. <https://doi.org/10.1287/mnsc.32.10.1231>
- Barney, Jay B. 1991. Firm Resources and Sustained Competitive Advantage. *Journal of Management* 17: 99–120. <https://doi.org/10.1177/014920639101700108>
- Barney, Jay B., Mike Wright, and David J. Ketchen. 2001. The Resource-Based View of the Firm: Ten Years after 1991. *Journal of Management* 27: 625–641. <https://doi.org/10.1177/014920630102700601>
- Chandler, Alfred D. 1962. Strategy and Structure: Chapters in the History of the Industrial Enterprise. *MIT Press*. <https://s3.amazonaws.com/arena-attachments/705027/a973f694aaee073aeb1cfce037f3b11.pdf>
- Cohen, Wesley M., and Daniel A. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly* 35: 128–152. <https://doi.org/10.2307/2393553>
- Csaszar, Felipe A., and Tom Steinberger. 2022. Organizations as Artificial Intelligences: The Use of Artificial Intelligence Analogies in Organization Theory. *Academy of Management Annals* 16: 1–37. <https://doi.org/10.5465/annals.2020.0192>
- D'Aveni, Richard A. and Robert Gunther. 1994. Hypercompetition: Managing the Dynamics of Strategic Maneuvering. *Free Press*: 83–93.
- Dierickx, Ingemar and Karel Cool. 1989. Asset Stock Accumulation and Sustainability of Competitive Advantage. *Management Science* 35: 1504–1511. <https://doi.org/10.1287/mnsc.35.12.1504>
- Doshi, Anil R., J. Jason Bell, Emil Mirzayev, and Bart S. Vanneste. 2025. Generative Artificial Intelligence and Evaluating Strategic Decisions. *Strategic Management Journal* 46: 583–610. <https://doi.org/10.1002/smj.3677>
- Dyer, Jeffery H., and Harbir Singh. 1998. The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage. *Academy of Management Review* 23: 660–679. <https://doi.org/10.5465/amr.1998.1255632>
- Eisenhardt, Kathleen M., and Jeffrey A. Martin. 2000. Dynamic Capabilities: What Are They? *Strategic Management Journal* 21: 1105–1121. [https://doi.org/10.1002/1097-0266\(200010/11\)21:10/11](https://doi.org/10.1002/1097-0266(200010/11)21:10/11)
- Felin, Toppo, Nicolai J. Foss, and Robert E. Ployhart. 2015. The Microfoundations Movement in Strategy and Organization Theory. *Academy of Management Annals* 9: 575–632. <https://doi.org/10.1080/19416520.2015.1007651>
- Foss, Nicolai J. 2011. Invited Editorial: Why Micro-Foundations for Resource-Based Theory Are Needed and What They May Look Like. *Journal of Management* 37: 1413–1428. <https://doi.org/10.1177/0149206310390218>
- Freeman, R. Edward and John Mcvea. 1984. Strategic Management: A Stakeholder Approach. *Pitman*. <https://onlinelibrary.wiley.com/doi/abs/10.1111/b.9780631218616.2006.00007.x>
- Furrer, O., H. Thomas, and A. Goussevskaia. 2008. The Structure and Evolution of the Strategic Management Field: A Content Analysis of 26 Years of Strategic Management Research. *International Journal of Management Reviews* 10: 1–23. <https://doi.org/10.1111/j.1468-2370.2007.00217.x>

- George, Gerard, Jennifer Howard-Grenville, Aparna Joshi, and Laszlo Tihanyi. 2016. Understanding and Tackling Societal Grand Challenges through Management Research. *Academy of Management Journal* 59: 1880–1895. <https://doi.org/10.5465/amj.2016.4007>
- Grant, Robert M. 1996. Toward a Knowledge-Based Theory of the Firm. *Strategic Management Journal* 17: 109–122. <https://doi.org/10.1002/smj.4250171110>
- Gregory, Robert Wayne, Ola Henfridsson, Evgeny Kaganer, and Harris Kyriakou. 2021. The Role of Artificial Intelligence and Data Network Effects for Creating User Value. *Academy of Management Review* 46: 534–551. <https://doi.org/10.5465/amr.2019.0178>
- Hart, Stuart L. 1995. A Natural-Resource-Based View of the Firm. *Academy of Management Review* 20: 986–1014. <https://doi.org/10.5465/amr.1995.9512280033>
- Helfat, Constance E., and Jeffrey A. Martin. 2015. Dynamic Managerial Capabilities: Review and Assessment of Managerial Impact on Strategic Change. *Journal of Management* 41: 1281–1312. <https://doi.org/10.1177/0149206314561301>
- Helfat, Constance E., and Margaret A. Peteraf. 2003. The Dynamic Resource-Based View: Capability Lifecycles. *Strategic Management Journal* 24: 997–1010. <https://doi.org/10.1002/smj.332>
- Hoskisson, Robert E., Lorraine Eden, Chung Ming Lau, and Mike Wright. 2000. Strategy in Emerging Economies. *Academy of Management Journal* 43: 249–267. <https://doi.org/10.5465/1556394>
- Hoskisson, Robert E., William P. Wan, Daphne Yiu, and Michael A. Hitt. 1999. Theory and Research in Strategic Management: Swings of a Pendulum. *Journal of Management* 25: 417–456. <https://doi.org/10.5465/1556394>
- Jacobides, Michael G., Carmelo Cennamo, and Annabelle Gawer. 2018. Towards a Theory of Ecosystems. *Strategic Management Journal* 39: 2255–2276. <https://doi.org/10.1002/smj.2904>
- Khanna, Tarun, and Krishna G. Palepu. 2010. Winning in Emerging Markets: A Road Map for Strategy and Execution. *Harvard Business Press*. <https://www.hbs.edu/faculty/Pages/item.aspx?num=37467>
- Korinek, Anton, and Joseph E. Stiglitz. 2021. Artificial Intelligence, Globalization, and Strategies for Economic Development. *National Bureau of Economic Research*:1–42. <https://doi.org/10.3386/w28453>
- Kraaijenbrink, Jeroen, J. C. Spender, and Aard J. Groen. 2010. The Resource-Based View: A Review and Assessment of Its Critiques. *Journal of Management* 36: 349–372. <https://doi.org/10.1177/0149206309350775>
- Krakovski, Sebastian, Johannes Luger, and Sebastian Raisch. 2023. Artificial Intelligence and the Changing Sources of Competitive Advantage. *Strategic Management Journal* 44: 1425–1452. <https://doi.org/10.1002/smj.3387>
- McGrath, Rita Gunther. 2013. The End of Competitive Advantage: How to Keep Your Strategy Moving as Fast as Your Business. *Harvard Business Review Press*.
- Mintzberg, Henry. 1978. Patterns in Strategy Formation. *Management Science* 24: 934–948. <https://doi.org/10.1287/mnsc.24.9.934>
- Mintzberg, Henry. 1994. The Rise and Fall of Strategic Planning. *The Academy of Management Review*. <https://doi.org/10.2307/258641>
- Mintzberg, Henry, Bruce Ahlstrand, and J. Lampel. 1998. Strategy Safari: A Guided Tour through the Wilds of Strategic Management. *Semantic Scholar*. <https://www.semanticscholar.org/paper/Strategy-safari-%3A-a-guided-tour-through-the-wilds-Mintzberg-Ahlstrand/4d4516900146db1dd5420910213085b166b5da7d>
- Mintzberg, Henry, and James A. Waters. 1985. Of Strategies, Deliberate and Emergent. *Strategic Management Journal* 6: 257–272. <https://www.jstor.org/stable/2486186>
- Nelson, Richard R., and Sidney G. Winter. 1982. An Evolutionary Theory of Economic Change. *The Business History Review* 57: 576–578. <https://doi.org/10.2307/3114818>
- Nonaka, Ikujiro. 1994. A Dynamic Theory of Organizational Knowledge Creation. *Organization Science* 5: 14–37. <https://doi.org/10.1287/orsc.5.1.14>
- North, Douglass C. 1990. Institutions, Institutional Change and Economic Performance. *Cambridge University Press*. <https://doi.org/10.1017/CBO9780511808678>
- Ocasio, William. 1997. Towards an Attention-Based View of the Firm. *Strategic Management Journal* 18: 187–206. [https://doi.org/10.1002/\(SICI\)1097-0266\(199707\)18:1](https://doi.org/10.1002/(SICI)1097-0266(199707)18:1)
- Peng, Mike W., Sunny Li Sun, Brian Pinkham, and Hao Chen. 2009. The Institution-Based View as a Third Leg for a Strategy Tripod. *Academy of Management Perspectives* 23: 63–81. <https://doi.org/10.5465/amp.2009.43479264>
- Peng, Mike W., Denis Y. L. Wang, and Yi. Jiang. 2008. An Institution-Based View of International Business Strategy: A Focus on Emerging Economies. *Journal of International Business Studies* 39: 920–936. <https://doi.org/10.1057/palgrave.jibs.8400377>
- Penrose, Edith. 1959. The Theory of the Growth of the Firm. *Oxford Academic*. <https://academic.oup.com/book/25306>
- Peteraf, Margaret A. 1993. The Cornerstones of Competitive Advantage: A Resource-Based View. *Strategic Management Journal* 14: 179–191. <https://www.jstor.org/stable/2486921>
- Pitelis, Christos N., David J. Teece, and Hongyi Yang. 2024. Dynamic Capabilities and MNE Global Strategy: A Systematic Literature Review-Based Novel Conceptual Framework. *Journal of Management Studies* 61: 3295–3326. <https://doi.org/10.1111/joms.13021>
- Porter, Michael E. 1980. Competitive Strategy: Techniques for Analyzing Industries and Competitors. Free Press. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1496175
- Porter, Michael E. 1985. Competitive Advantage: Creating and Sustaining Superior Performance. *Harvard Business School*. <https://www.hbs.edu/faculty/Pages/item.aspx?num=193>

- Porter, Michael E., and Mark R. Kramer. 2011. Creating Shared Value. *Harvard Business Review* 89: 62–77. <https://hbr.org/2011/01/the-big-idea-creating-shared-value>
- Priem, Richard L., and John E. Butler. 2001. Is the Resource-Based 'View' a Useful Perspective for Strategic Management Research? *Academy of Management Review* 26: 22–40. <https://doi.org/10.2307/259392>
- Raisch, Sebastian and Kateryna Fomina. 2025. Combining Human and Artificial Intelligence: Hybrid Problem-Solving in Organizations. *Academy of Management Review* 50: 441–464. <https://doi.org/10.5465/amr.2021.0421>
- Raisch, Sebastian, and Sebastian Krakowski. 2021. Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review* 46: 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Ronda-Pupo, Guillermo Armando, and Luis Ángel Guerras-Martín. 2012. Dynamics of the Evolution of the Strategy Concept 1962–2008: A Co-Word Analysis. *Strategic Management Journal* 33: 162–188. <https://doi.org/10.1002/smj.948>
- Rumelt, Richard P., Dan E. Schendel, and David J. Teece. 1994. Fundamental Issues in Strategy: A Research Agenda. *Administrative Science Quarterly* 41: 196–198. <https://doi.org/10.2307/2393999>
- Sirmon, David G., Michael A. Hitt, R. Duane Ireland, and Brett Anitra Gilbert. 2011. Resource Orchestration to Create Competitive Advantage: Breadth, Depth, and Life Cycle Effects. *Journal of Management* 37: 1390–1412. <https://doi.org/10.1177/0149206310385695>
- Snyder, Hannah. 2019. Literature Review as a Research Methodology: An Overview and Guidelines. *Journal of Business Research* 104: 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Teece, David J. 2007. Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strategic Management Journal* 28: 1319–1350. <https://doi.org/10.1002/smj.640>
- Teece, David J. 2010. Business Models, Business Strategy and Innovation. *Long Range Planning* 43: 172–194. <https://doi.org/10.1016/j.lrp.2009.07.003>
- Teece, David J. 2014. The Foundations of Enterprise Performance: Dynamic and Ordinary Capabilities in an (Economic) Theory of Firms. *Academy of Management Perspectives* 28: 328–352. <https://doi.org/10.5465/amp.2013.0116>
- Teece, David J., Gary Pisano, and Amy Shuen. 1997. Dynamic Capabilities and Strategic Management. *Strategic Management Journal* 18: 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7)
- Torraco, Richard J. 2005. Writing Integrative Literature Reviews: Guidelines and Examples. *Human Resource Development Review* 4: 356–367. <https://doi.org/10.1177/1534484305278283>
- Townsend, David M., Richard A. Hunt, Judy Rady, Parul Manocha, and Ju Hyeong Jin. 2025. Are the Futures Computable? Knightian Uncertainty and Artificial Intelligence. *Academy of Management Review* 50: 415–440. <https://doi.org/10.5465/amr.2022.0237>
- Vaara, Eero, and Richard Whittington. 2012. Strategy-as-Practice: Taking Social Practices Seriously. *Academy of Management Annals* 6: 285–336. <https://doi.org/10.1080/19416520.2012.672039>
- Verhoef, Peter C., Thijis Broekhuizen, Yakov Bart, Abhi Bhattacharya, John Qi Dong, Nicolai Fabian, and Michael Haenlein. 2021. Digital Transformation: A Multidisciplinary Reflection and Research Agenda. *Journal of Business Research* 122: 889–901. <https://doi.org/10.1016/j.jbusres.2019.09.022>
- Volberda, Henk W., Saeed Khanagha, Charles Baden-Fuller, Oli R. Mihalache, and Julian Birkinshaw. 2021. Strategizing in a Digital World: Overcoming Cognitive Barriers, Reconfiguring Routines and Introducing New Organizational Forms. *Long Range Planning* 54: 102110. <https://doi.org/10.1016/j.lrp.2021.102110>
- Krogh, G von. 2018. Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing. *Academy of Management Discoveries* 4: 404–409. <https://doi.org/10.5465/amd.2018.0084>
- Warner, Karl S. R., and Maximilian Wager. 2019. Building Dynamic Capabilities for Digital Transformation: An Ongoing Process of Strategic Renewal. *Long Range Planning* 52: 326–349. <https://doi.org/10.1016/j.lrp.2018.12.001>
- Wernerfelt, Birger. 1984. A Resource-Based View of the Firm. *Strategic Management Journal* 5: 171–180. <https://doi.org/10.1002/smj.4250050207>
- Whittington, Richard. 1996. Strategy as Practice. *Long Range Planning* 29: 731–735. [https://doi.org/10.1016/0024-6301\(96\)00068-4](https://doi.org/10.1016/0024-6301(96)00068-4)
- Wright, Mike, Igor Filatotchev, Robert E. Hoskisson, and Mike W. Peng. 2005. Strategy Research in Emerging Economies: Challenging the Conventional Wisdom. *Journal of Management Studies* 42: 1–33. <https://doi.org/10.1111/j.1467-6486.2005.00487.x>