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Organizational AI Capability: From Algorithmic Capital to Sustainable Competitive Advantage

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Abstract:

The pace of artificial intelligence (AI) across industries has created a paradox: numerous organizations purchase AI technologies and even build up an arsenal of algorithms, yet many fail to transform this purchase into sustainable benefit. The construct that is most frequently called upon to give an explanation of this gap- AI capability- is still conceptually disjointed. Earlier literature has focused on adoption, preparation, maturity, and resource collection, and a parallel line has started to consider algorithmic assets as a specific strategic resource (algorithmic capital). The transformation, i.e., how organizations transform algorithmic capital and other resources into a higher-order organizational AI capability, and why that capability should be able to create value, is what is unspecified. The present paper builds up an integrative transformation theory based on the Resource-Based View, the Knowledge-Based View, the Dynamic Capabilities perspective, and Organizational Learning theory. We characterize the organizational AI capability as a higher-order, multidimensional construct; present a three-level architecture that bridges AI resources (including algorithmic capital), mid-level capability constructs, and an emergent organizational capability; describe a formation mechanism; develop seven propositions; and state the boundary conditions. The contribution is a coherent account of how firms move from possessing algorithmic capital to possessing an AI-based organizational capability, and from that capability to competitive advantage.

Keywords: organizational AI capability; algorithmic capital; resource-based view; knowledge-based view; business engineering; competitive advantage.

1. Introduction

Artificial intelligence ceased to be a niche field of research and became a general-purpose technology in the company (Brynjolfsson & McAfee, 2014; Iansiti & Lakhani, 2020). This change has been accelerated by the recent spread of generative AI and is placing greater pressure on organizations of all sizes to transform processes, decisions, and business models with the help of AI (Rajaram & Tinguely, 2024; Storey et al., 2025). Companies are currently implementing machine learning, natural-language systems, and generative models across their operations, marketing, strategy, and human resources, with widespread impacts anticipated on productivity and innovation (Cockburn et al., 2018; Prasad Agrawal, 2024; Ransbotham et al., 2017). Its spread is widely dispersed, rapid, and mostly irreversible: AI has become a norm and not a point of difference.

But diffusion has surpassed comprehension. The term AI capability is commonly used by practitioners and scholars to explain why certain organizations achieve disproportionately higher returns from AI than others do not, or why pilots put stalling on the agenda (Mikalef & Gupta, 2021). However, this term is used vaguely and inconsistently. To others, it reflects technical infrastructure; to others, data resources, analytical skills, governance maturity, or even the adoption process. This intellectual elasticity undermines cumulative theory: when the construct has different meanings among writers, there is no way to compare empirical results, and prescriptions to managers are based on sand.

Three problems follow. The first one is definitional plurality: there is no common definition of organizational AI capability. Second, level confusion: the higher-order capability, resources, and components are often confused. Third, there is a lack of a theory of transformation that explains how capability is shaped from the underlying resources and why it is supposed to be advantageous. The three are discussed in this paper.

This is our theoretical aim. We do not test hypotheses; we create a framework. To be more precise, we (1) operationalize organizational AI capability as a higher-order construct, (2) identify a three-level architecture, (3) describe a formation mechanism, (4) testable propositions, and (5) scope conditions explicitly. The contribution to be made is a coherent conceptual basis that can be operationalized and tested in the future by empirical studies.

2. The Theoretical Problem

There is a mass of literature on AI in organizations but a conceptual imbalance. There are a number of streams that prevail, such as AI adoption (Alsheibani et al., 2018), AI readiness and digital transformation (Agarwal et al., 2010), big data and analytics capability (Mikalef et al., 2019), and AI

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resources reframed as algorithmic capital (Abuhaimed, 2026b), and each of them sheds light on the phenomenon without answering the constitutive question.

Table (1). Conceptual Distinctions Among AI Adoption, Readiness, Maturity, and Resource-Based Perspectives

Research Stream	What It Explains — and What It Leaves Open
AI Adoption	Explains how AI is decided to be acquired and implemented. Takes AI as a phenomenon, not a skill; says little about what the firm can subsequently do with it
AI Readiness	Evaluates the preconditions (data, skills, leadership) prior to deployment. Diagnostic and static; refers to possible, but unrealized ability.
AI Maturity	Places firms on a developmental ladder (Sonntag et al., 2024; Khan et al., 2025). Descriptive and usually atheoretical; denotes levels without a causal process of formation.
AI Resources / Algorithmic Capital	Inventories and (recently) redefines AI resources -data, models, compute, talent, algorithmic capital. Necessary and not sufficient; having is not being able.

As summarized in the table above, these literature streams provide answers to useful yet incomplete questions: whether to adopt AI, whether a firm is ready, how mature its AI deployment is, and what AI-related resources it possesses. None of them responds to the constitutive question which drives this paper:

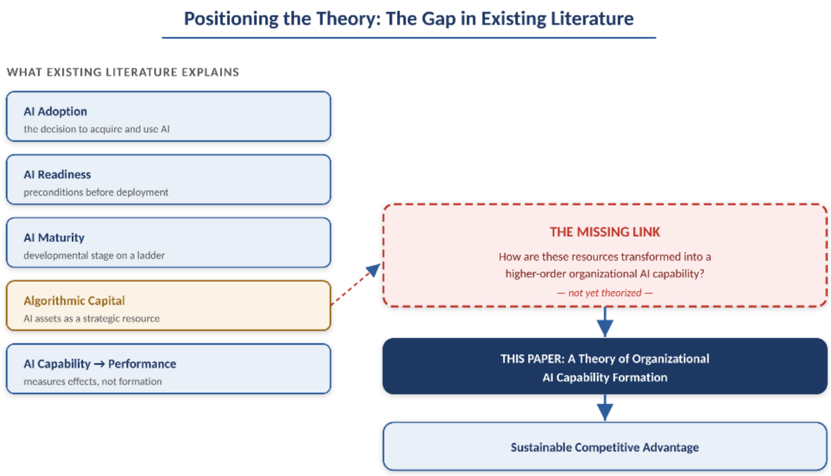
What constitutes organizational AI capability, and how is it formed from algorithmic capital?

It should be answered by differentiating between the possession of AI resources and the performing of AI: the ability to organize, assimilate, and redesign AI resources into repetitive, value-producing organizational activity. The conceptual fault line the rest of the paper evolves is that difference.

Recent literature has begun to consider AI capability as a performance-relevant strategic construct. Empirical papers associate AI potential with firm performance, creativity, and quality of decisions (Mikalef & Gupta, 2021; Neiroukh, Emeagwali & Aljuhmani, 2024), and conceptualize it in terms of dynamic capabilities (Abou-Foul et al., 2023). A parallel maturity literature phases the deployment of AI by companies over time (Sonntag et al., 2024; Khan et al., 2025), and a governance literature looks at how AI should be responsibly regulated once deployed (Papagiannidis, Mikalef, & Conboy, 2025). This article confirms the importance of AI capabilities- but it mostly quantifies its impacts, rather than describing how it is formed.

It is the key to the gap, and it is not just empirical. Current explanations fail to explain how AI capability of organizations is formed due to three structural reasons. To start with, most of the literature conflates levels and resources; mid-level competencies and higher-order capabilities are treated as one homogeneous bundle, rendering the process of transformation between them inconspicuous. Second, capability is commonly quantified as a reflective latent variable that is correlated with performance; a black-box approach that quantifies the presence of capability but not the interaction of its components to form it. Third, the prevailing framing is a static, possession-based one: it catalogs what high-capability firms possess rather than how the dynamic, recursive process of integrating and reconfiguring resources into capability occurs over time. Put briefly, current literature describes the adoption, readiness, governance, and algorithmic capital in isolation and shows that the former is a valuable capability, yet none of them define how this transformation should take place. This is what is covered in this paper.

Figure (1). Theoretical Gap in the Formation of Organizational AI Capability



Existing streams explain AI adoption, readiness, maturity, algorithmic capital, and the effects of capability, but none explains how resources are transformed into a higher-order organizational AI capability. This paper addresses that missing link.

2.1 Conceptual Limitations of Existing AI Capability Frameworks

It is worth noting what it is and is not given by the most influential extant accounts, as the current theory is in part characterized by opposition to them. The most-cited treatment in the field, by Mikalef

& Gupta (2021), conceptualizes and measures AI capability as a multidimensional resource bundle and shows its relationship with creativity and firm performance; their contribution is to show that AI capability is important and how it can be measured, but the construct itself is modeled as a reflective composite, the internal formation of which is not theorized. Abou-Foul et al. (2023) develop a dynamic-capabilities reading that connects AI capability to servitization, but does not define how reconfiguration occurs within an organization. Preconditions and developmental stages are described by the AI readiness and AI maturity literatures (Alsheibani et al., 2018; Sonntag et al., 2024; Khan et al., 2025), but by definition, they chart the position of a firm instead of how it gets there.

In these descriptions, a similar constraint re-emerges: both authors describe AI capability as a state to be quantified or performed, and no one describes the generative process that transforms underlying resources into the capability in the first place. The current theory is placed at this very omission. It does not contest that AI capability is valuable, multidimensional, or developmental; it describes what those descriptions leave undecided: the architecture in which resources are made components, the integration that makes components integrated into a higher-order capability, and the organizational redesign that makes the integration possible. In a word, where the previous approaches will answer the question of what is AI capability and does it pay off, this theory will answer the question of how it is created.

3. Study Methodology:

This study adopts a conceptual, theory-building approach based on an integrative review and synthesis of the relevant literature. Rather than testing predefined hypotheses using primary empirical data, the study seeks to develop a coherent theoretical explanation of how organizational AI capability emerges from underlying AI resources, particularly algorithmic capital, and how such capability may contribute to sustainable competitive advantage. The analysis integrates complementary theoretical perspectives from the Resource-Based View, Knowledge-Based View, Dynamic Capabilities perspective, and Organizational Learning theory to identify the mechanisms through which AI-related resources are organized, assimilated, reconfigured, and transformed into a higher-order organizational capability.

The study relies on secondary scholarly sources, including peer-reviewed research on AI capability, AI adoption, AI readiness, AI maturity, algorithmic capital, and related organizational and strategic capabilities, together with foundational theoretical works in the four underlying theoretical perspectives. These streams of literature are comparatively examined to clarify conceptual boundaries, identify limitations in existing explanations, and establish relationships among resource inputs, intermediate capability constructs, and organizational-level AI capability. This integrative synthesis provides the basis for developing the proposed three-level capability architecture, the underlying formation mechanism, the theoretical propositions, and the boundary conditions of the framework.

4. Theoretical Foundations

Four complementary theories are synthesized in this study. Each of them, separately, is not complete to the AI context; a combination of them provides the bricks of a transformation theory of organizational AI capability.

4.1 Resource-Based View (RBV)

The RBV is based on the premise that sustained advantage is achieved through resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991; Peteraf, 1993). When applied to AI, the RBV explains why raw assets, including data, models, compute, and even accumulated algorithmic capital, are needed but rarely made: most of them are tradable, replicable, or commoditized. Benefit should therefore not be in the assets per se but in the combination and deployment of the assets. The RBV thus shifts the focus of attention away from algorithmic capital to the bundling of that capital that is firm-specific.

4.2 Knowledge-Based View (KBV)

The KBV is an expansion of the RBV which considers knowledge as the most strategically important resource of the firm and the firm as an institution of combining specialized knowledge (Grant, 1996; Nonaka, 1994). AI capability is knowledge-intensive: it relies on tacit knowledge of problem formulation, model interpretation, and the translation of predictions into decisions. The KBV describes why AI value is difficult to copy-most of the related knowledge is tacit, socially complicated, and embedded in routines- and why the integration of knowledge between data, technical, and domain experts is at the heart of capability.

4.3 Dynamic Capabilities

Dynamic capabilities refer to the firm's ability to detect opportunities, grab them, and restructure its resource base in a dynamic environment (Teece et al., 1997; Teece, 2007). Due to the fast rate of evolution of AI technologies, a fixed pool of algorithmic capital decays fast. The dynamic-capabilities lens provides the reconfiguration aspect of our definition: organizational AI capability is not a given endowment but a higher-order, and renewable (Winter, 2003) ability to perceive new AI opportunities, to grasp them by implementation, and to adapt routines to them.

4.4 Organizational Learning

The theory of organizational learning describes the process of transforming experience into better routines by exploration, exploitation, and feedback (March, 1991; Argyris and Schön, 1978). The nature of AI capability is iterative: models are trained, tested, refined, and deployed. The perpetual improvement loop explained by the learning theory explains the difference between a capability and a one-off project and the basis of the argument that AI capability accrues over time as the organization learns how to learn with AI. To clarify the theoretical foundations of the proposed organizational AI capability construct, Table 2 summarizes the distinct contribution of each underlying theoretical perspective. Together, these perspectives explain how AI-related resources are mobilized, integrated, reconfigured, and progressively developed into a higher-order organizational capability.

Table (2). Theoretical Building Blocks of Organizational AI Capability

Theory	Building Block It Contributes to the Construct
RBV	Firm-specific bundling of algorithmic capital and other AI resources as the locus of advantage (mobilize/integrate).
KBV	Integration of specialized, tacit knowledge as the source of inimitability.
Dynamic Capabilities	Sensing, seizing, and reconfiguring AI resources under technological change.
Organizational Learning	Iterative feedback loops that let the capability compound over time.

4.5. The Business Engineering Premise as a Mechanism of Organizational Reconfiguration

The four above theories clarify that resources have to be bundled, knowledge integrated, capabilities reconfigured, and routines learned, but they are silent on how this can be effected by the organization. Dynamic-capabilities theory, in particular, assumes sensing, seizing, and reconfiguring but treats reconfiguration as managerial and does not specify the internal machinery; it describes the functionality but not the mechanism. It is this that a Business Engineering premise fills.

Business Engineering believes that design is a way of building organizational ability: by re-engineering the structures, processes, decision authority, governance, and digital architecture. This is not a unique premise; it is based on a long tradition in organizational and information-systems scholarship. Organizational-design theory is that performance is a consequence of the calculated fit between strategy, structure, processes, rewards, and people (Galbraith, 1977), and sociotechnical-systems theory is that value can only be created when the social and technical subsystems are both optimized by redesign as opposed to being treated as distinct systems (Bostrom & Heinen, 1977). Business Engineering is a design logic applied to the AI context (Abuhaimed, 2026a). Here, it defines what reconfiguration really means within the AI context, not an abstract managerial act but the real redesign of the arrangement of work, decisions, and accountability around AI. Two companies can have the same dynamic-capability potential but go in completely different directions since only one company has designed its organization to transform its potential into a functional capability. The Business Engineering in this theory thus is not a fifth lens to complete the picture but the working mechanism that renders the other four lenses consequential. Take it away, and the theory is able to explain the inputs and the outcome but not the change that occurs between the two- the phenomenon that it is intended to explain.

4.6 Algorithmic Capital as the Foundational Resource

Since this theory describes how algorithmic capital is converted to capability, the antecedent construct needs to be defined very specifically, and then the capability erected on the antecedent construct. The paper embraces the conception created in the resource-based and intellectual-capital literatures (Abuhaimed, 2026b).

Algorithmic capital. Algorithmic capital is a stock of proprietary algorithms, trained and fine-tuned models, learning architectures, and embedded algorithmic knowledge that an organization can strategically manage and use to create value.

Three ontological clarifications cement its position in the architecture and avert the level confusion which undermines previous work:

1. It is not an ability, but a resource. Algorithm capital is a stock that is owned or controlled by the firm- an input to be mobilized. It is at Level 1 of the architecture, together with data, infrastructure, and talent. It does not do anything, in itself.
2. It is not a capability . A capability is a flow - a power to act and recombine. Having advanced models does not equate to the capacity to integrate, control, and reorganize them in an organization. This is the difference between the two that is theorized in this paper.
3. It is not an outcome. Algorithm capital is neither value created nor competitive advantage achieved: it is the downstream consequences of the capability with the resource. Considering algorithmic capital as a conclusion would render the causal path the theory constructs a failure.

Simply put, algorithmic capital is the strategically unique input of the AI age. It only needs to accumulate, but not enough; it benefits when it is changed by the capability components into a higher-order organizational AI capability. It is the hinge of the theory that rests on this conceptual idea.

5. Defining Organizational AI Capability

Based on these, the study presents a key theoretical definition that brings together the four lenses of mobilization (RBV), integration (KBV), governance and reconfiguration (dynamic capabilities), which are maintained through learning.

Definition. *The organizational AI capability is the organizational ability to mobilize, integrate, govern and reconfigure AI-related resources, such as its algorithmic capital, in order to produce sustainable organizational value.* Four features warrant emphasis:

1. Higher-order and emergent. It is not a resource or skill, but a capacity that arises from the interplay of lower-order components; it cannot be broken down to any of them.
2. Multidimensional. It cuts across data, technical, governance, learning, and integration dimensions, none of which is sufficient in their own right.
3. Dynamic. The term continuously reconfigure incorporates renewal: the ability will evolve with the changes in AI technologies and competitive circumstances.
4. Value-oriented. It is characterized by its product sustainable organizational value rather than by activity or ownership of assets.

5.1. A Concept Matrix: Distinguishing AI Capability from Adjacent Constructs

Since the organizational AI capability can be easily mixed with readiness, adoption, maturity, resources, and competence, we clarify the differences. The next concept matrix positions each of the constructs according to its place in the AI lifecycle and its conceptual nature to isolate what is unique to capability.

Table (3). Conceptual Positioning of AI-Related Constructs Across the Organizational AI Lifecycle

Construct	Lifecycle Position	Nature	Core Question
AI Readiness	Before AI	Potential (static)	Are the preconditions in place?
AI Resources / Algorithmic Capital	Input stock	Asset (stock)	What does the organization own or control?

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Construct	Lifecycle Position	Nature	Core Question
AI Adoption	Initial use	Event (discrete)	Has the organization begun to use AI?
AI Maturity	Development stage	Stage (descriptive)	How far along a developmental ladder is it?
AI Competence	Component skill	Skill (mid-level)	Can the organization perform a specific AI task well?
AI Capability	Organizational competence	Higher-order, dynamic (flow)	What can the organization repeatedly *do* with AI to create sustainable value? — the focus of this paper.

The hierarchy of concepts is explained by the matrix: readiness and resources are antecedents; adoption is an event; maturity is a descriptive concept; competence is a mid-level skill (equivalent to a single component of competence). The higher-order dynamic competence that combines these into a value-creating whole- organizational AI capability- is a flow, not a stock, and the sole construct in the matrix of sustainable value creation.

The proposed capability components, which include data, technical aspects, governance, learning, and integration, come from the theoretical synthesis outlined in this paper instead of being chosen randomly. Together, they constitute the main organizational mechanisms that transform AI resources, including algorithmic capital, into a more advanced organizational AI capability. Other factors such as leadership and organizational culture serve as background elements that support capability development rather than being part of the capability itself.

This theory focuses on the organizational level of analysis. While individual AI skills, leadership, and organizational culture affect how capabilities develop, they are seen as background factors rather than essential parts of organizational AI capability.

6. Capability Architecture

This study defines organizational AI capability as a three-tier hierarchy, illustrated in Figure 1. Each level serves as input to the level above it; the higher-order capability is a product of but not identical with the aggregate of its components.

Level 1 — AI Resources, including Algorithmic Capital (foundational layer)

The raw inputs are the resources. In line with the RBV, they are essential but not sufficient in themselves to be capabilities. We consider algorithmic capital to be a separate category of resources of the firm as the accumulated and strategically managed stock of algorithmic assets in addition to the traditional inputs (Abuhaimed, 2026b).

1. Algorithmic capital - proprietary algorithms, trained and fine-tuned models, and embedded algorithmic knowledge, which is a strategic asset that is governable (defined in Section 3.6).
2. Data - amount, types, quality, and accessibility of information that AI systems are taught.
3. Infrastructure - compute, storage, pipelines, and tooling to actualize AI.
4. Talent: data scientists and engineers, and domain experts to design and maintain AI systems.

Level 2 — AI Capability Components (integrative layer)

Components transform resources to deployable competence. Both of them are intermediate abilities. After considering the relevance of reviewers, we break down integration, which used to be an umbrella-like catch-all, into three sub-capabilities.

Table (4). Multidimensional Structure of Organizational AI Capability

Component	Definition
Data Capability	Acquiring, cleaning, governing, and provisioning high-quality data for AI use.
Technical Capability	Building, deploying, monitoring, and maintaining performant AI models and pipelines.
Governance Capability	Managing risk, ethics, compliance, security, and accountability across the AI lifecycle (Papagiannidis et al., 2025)—extending the governance of algorithmic capital to the capability level.
Learning Capability	Capturing feedback and experience to iteratively improve models and routines.
Integration Capability	Embedding AI into the organization. Decomposed into three sub-capabilities (below).

Decomposing Integration Capability

Table (5). Decomposition of AI Integration Capability into Sub-Capabilities

Sub-capability	Definition
Process Integration	Embedding AI into operational and business processes so it runs as part of normal work, not as a side experiment.
Decision Integration	Connecting AI outputs to managerial and operational decision rights so predictions reliably inform or trigger decisions.
Workflow Integration	Aligning AI with human roles, hand-offs, and tooling so people and systems act on AI outputs without friction.

Disaggregating integration in this way prevents it from silently absorbing the explanatory burden of the whole model and yields finer, separately testable predictions about where integration most often fails.

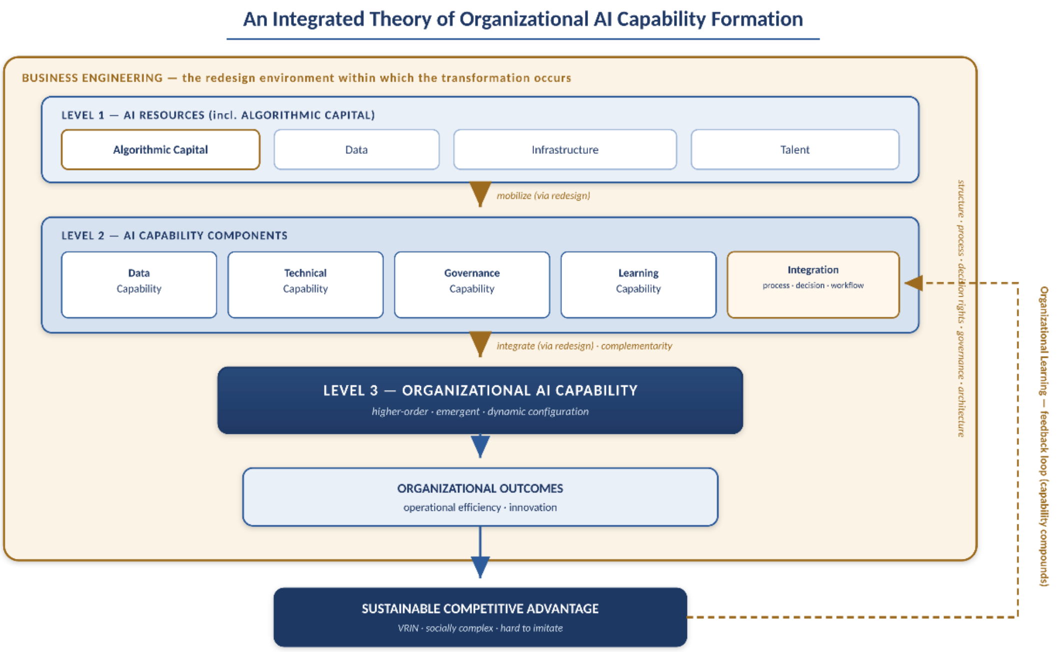
Level 3 — Organizational AI Capability (emergent layer)

At the top, the components merge and co-specialize into a greater-order organizational AI capability. This new capability is more than the sum of its parts: its value lies in the complementarities between them (Mikalef & Gupta, 2021) - strong data capability is squandered without integration; technical excellence is weak without governance; none compounds without learning. This socially complex and firm-specific arrangement meets the VRIN conditions and is the basis of advantage.

7. Capability Formation Mechanism

In what ways is the higher-order capability formed? Our four-stage causal chain starts with algorithmic capital and other resources, breaks them down into components, organizes the organizational capability, and produces outcomes that feed back as learning. More importantly, all of the transformation is within a Business Engineering environment: the levels are not related but rather are related through the intentional re-designing of structure, process, decision rights, governance, and architecture. Get rid of that setting, and the arrows lack a medium through which resources become capability. Business Engineering is not thus a complementary lens but the facilitating state of the mechanism.

Figure (2). An Integrated Model of Organizational AI Capability Formation through Business Engineering



From figure 2. We found the organizational AI capability forms only inside the Business Engineering environment: the redesign of structure, process, decision rights, governance, and architecture is the medium through which resources are mobilized and integrated into a higher-order capability.

This is a mechanism and not a checklist due to two characteristics. The decisive change is first that of integration: algorithmic capital is not created spontaneously; it has to be integrated into managerial and organizational work in processes, decisions, and workflow. Second, it is a recursive loop: results and the process of their creation are looped back through the organizational learning to improve resources and elements. The ability hence builds up, which is why early movers who are effective learners are able to build on their advantage, as opposed to retaining it.

That is why it is not only technical implementation but integration, and why the mechanism is not a data pipeline and model deployment. The shift to algorithmic capital to capability is essentially a redesign of processes: processes need to be re-architected to enable AI to run within normal work, decision rights re-allocated to enable prediction to take action, governance structures put in place, and organizational architecture re-designed around AI-enhanced routines. This design logic (Abuhaimed, 2026a) is the business engineering point of view, and in the current theory it is not an extrinsic complement, but rather the connective tissue of the formation mechanism--the layer (illustrated in Figure 2 with the transformation column) on which the elements of the integration are to do their work.

The components are latent, the algorithmic capital is a dormant stock, without conscious redesign; and the components co-specialize, becoming a higher-order capability.

7.1 An Illustrative Example

In order to base the mechanism, two firms that have the same algorithmic capital, that is, they are the same in terms of demand-forecasting models, similar data, and engineering talent, are considered. Firm A is a user of the model: analysts submit it, send the forecasts via email, and planners decide whether to act. Firm B re-engineers around it: flow is directly forecasted into replenishment workflows (process integration), definite reordering decisions within specified tolerances (decision integration), and re-train planner functions towards handling exceptions (workflow integration); a governance layer catches drift and bias, and a learning loop retrains the model on actual results. In a year, the forecasts in Firm B are more quickly improved, its planners believe them, and they are not easily imitated by competitors- because what makes Firm B unique is not the model but the social complex system around it. The same algorithmic capital, divergent capability: it is precisely that gap which the theory describes.

8. Theory Statement

A complete theory specifies what is related, how, why, and when. We summarize the theory along these four dimensions as in following table.

Table (6). Core Theoretical Dimensions of Organizational AI Capability Formation

Dimension	Theoretical Content
WHAT	The elements of the capability: data, technical, governance, learning, and integration (process/decision/workflow) capabilities, based on AI resources such as algorithmic capital.
HOW	The relationships: components interact with each other in a complementary way; integration turns algorithmic capital into capability; the structure is emergent and higher-order.
WHY	Algorithmic capital is transformed into capability by organizational redesign (Business Engineering) that brings the components together into a socially complex, VRIN configuration; a configuration that is resistant to imitation, value-generating, and compounded by learning loops.

Dimension	Theoretical Content
WHEN	The theory is most strongly true when AI is strategically material, algorithmic capital and data are meaningfully exploitable, and competitive imitation is non-trivial (see Section 9).

The table summarizes the theory through four complementary dimensions. It specifies what constitutes organizational AI capability, how its components interact and combine, why Business Engineering enables the transformation of AI resources into a higher-order capability, and when these mechanisms are most likely to generate sustainable competitive advantage. Together, these dimensions position the theory as an explanatory account of capability formation rather than a descriptive classification of AI-related activities.

9. Propositions

The theory provides seven propositions linking the resources, components, the higher-order capability, learning, and advantage. They are all based on an overt theoretical assumption, which is made right at the beginning of the proposition, such that the proposition is a logical deduction and not an assertion. Each of them is put in a way that can be empirically tested. Each proposition is first mapped to its grounding theory and logic as in Table 1, and then the propositions and their premises are presented.

Table (7). Theoretical grounding of the propositions.

Prop.	Grounding Theory	Theoretical Logic	Source
P1	Resource-Based View	Resources create value through firm-specific bundling, not possession → effect runs through components.	Barney (1991)
P2	Knowledge-Based View	Capability integrates distinct specialized knowledge domains; each necessary, none sufficient alone.	Grant (1996)
P3	Higher-Order · Dynamic Capabilities · Business Engineering	Emergence exceeds the additive sum, but only integration (process/decision/workflow redesign)	Winter (2003); Teece (2007);

Prop.	Grounding Theory	Theoretical Logic	Source
		produces the complementarities that bind components.	Abuhaimed (2026a)
P4	Organizational Learning	Experience improves routines via exploration–exploitation, yielding path-dependent accumulation.	March (1991)
P5	Governance · Value Capture	Appropriability requires managing risk and legitimacy; binding under regulatory/reputational exposure.	Abuhaimed (2026b)
P6	RBV Performance Link	Capability affects advantage via intermediate outcomes (efficiency, innovation).	Mikalef & Gupta (2021)
P7	VRIN · Causal Ambiguity	Causally ambiguous, socially complex sources resist imitation; tacit integration qualifies, tradable assets do not.	Barney (1991); Peteraf (1993)

Grounding (RBV). Resource-based view believes that resources can only provide benefit when combined and utilized in ways unique to a firm, rather than by ownership (Barney, 1991). This implies that AI resources must influence the capability by changing the organizational elements that transform it.

P1. Organizational AI capability has a positive relationship with AI resources such as algorithmic capital, data, infrastructure, and talent, but is completely mediated by the capability components and not direct.

Grounding (KBV · complementarity). The reasoning based on knowledge views capability as the combination of different specialized bodies of knowledge (Grant, 1996); none of the bodies can be dispensed with, but each is essential to the entirety.

P2. Data, technical, governance, learning and integration capabilities are all required but individually inadequate conditions to organizational AI capability.

Grounding (higher-order capabilities · dynamic capabilities · Business Engineering). The higher-order capabilities are emergent configurations the value of which lies in the interaction of the lower-order elements and not their sum (Winter, 2003; Mikalef and Gupta, 2021); however, the interaction does not come on its own, reconfiguration is necessitated by the mechanisms that re-package the resources into action (Teece, 2007), and the redesign of process, decision, and workflow is the organizational mechanism that generates the complementarities (Abuhaimed, 2026a). Emergence and integration are therefore two aspects of the same assertion: the higher-order capability is only as great as the integration among the components.

P3. The value of organizational AI capability is a higher-order construct whose value is more than the sum of its components, and this emergence is created by integration capability: complementarities among the components emerge as process, decision, and workflow integration tie them together, and thus the value of AI resources to capability increases with integration. Without integration, the components can only be additive and no higher-order capability is created.

Grounding (organizational learning). Through repeated exploration-exploitation processes, learning converts experience into better routines, resulting in path-dependent accumulation with time (March, 1991).

P4. The capability of learning enhances the organizational AI capability with time, yielding a compounding (path-dependent) curve, instead of a level curve.

Governance (grounding · RBV value capture). The ability to capture value is not guaranteed by the ability to capture risks, but by legitimacy, which is binding in the case of regulatory or reputational exposure (Papagiannidis et al., 2025; Abuhaimed, 2026b).

P5. There is a moderating effect of governance capability: in the case of high regulatory or reputational risk, AI capability needs governance capability to translate into sustainable value.

Grounding (RBV performance link). Capabilities affect benefit by initially enhancing the interim organizational performance in terms of efficiency and creativity, which are then converted into competitive position (Mikalef & Gupta, 2021).

P6. Organizational AI capability is positively linked to competitive advantage, with the intermediary of organizational outcomes of operational efficiency and innovation.

Grounding (VRIN · causal ambiguity). This is maintained when its sources are causally ambiguous and socially complex, and thus resistant to imitation; this is the case of tacit integration, but not with tradable assets (Barney, 1991; Peteraf, 1993).

P7. The competitive advantage of organizational AI capability is more sustainable (less prone to imitation) the greater the capability is based on tacit, socially complex integration than based on tradable algorithmic capital and other AI resources.

Table (8). Summary of propositions by relationship type, clarifying the theory's logical structure for empirical testing.

Prop.	Relationship Type	Core Claim (abbreviated)
P1	Mediation	Resources → capability, fully mediated by components.
P2	Necessity	Each component necessary but individually insufficient.
P3	Higher-order / emergence via integration	Integration produces complementarities that exceed the additive sum.
P4	Dynamic / path dependence	Learning makes capability compound over time.
P5	Moderation	Governance conditions capability → value under risk.
P6	Mediation	Capability → advantage, mediated by outcomes.
P7	Sustainability condition	Tacit integration makes advantage harder to imitate.

10. Toward Operationalization

To test the propositions, the constructs should be measurable. Table 3 provides a preliminary operationalization, indicating the focus of definition and candidate indicators of each component of capability that a future instrument-development effort can hone and confirm. The indicators are not comprehensive, but they provide a baseline in developing the scale in line with the higher-order, reflective-formative structure as described in Section 11.

Table (9). Candidate operationalization of the capability components.

Component	Candidate Indicators (illustrative)
Data Capability	Data quality and completeness; breadth of accessible sources; maturity of data governance and pipelines; speed of provisioning data for new use cases.
Technical Capability	Ability to build, deploy, and maintain models in production; monitoring and retraining practices; model performance and reliability; engineering throughput.

Component	Candidate Indicators (illustrative)
Governance Capability	Presence and use of risk, ethics, and compliance controls; bias and drift; accountability and audit mechanisms across the AI lifecycle.
Learning Capability	Frequency and structure of feedback capture; rate of model and routine improvement; institutionalization of lessons; experimentation cadence.
Integration — Process	Degree to which AI is embedded in standard operational processes rather than run as isolated pilots.
Integration — Decision	Extent to which AI outputs are connected to defined decision rights and reliably inform or trigger decisions.
Integration — Workflow	Alignment of AI with human roles, hand-offs, and tooling so people act on outputs without friction.
Organizational AI Capability (higher-order)	Modeled as a second-order construct composed of the components above; assessed via their joint presence and the firm's demonstrated ability to repeatedly generate value from AI.

Two cautions apply. To start with, since the higher-order construct is not represented by its components, it is reasonable to use a formative (or reflective-formative) measurement model, and the components cannot be thought of as interchangeable. Second, a number of indicators (particularly of learning and integration) are tacit in part, and may require perceptual or longitudinal data, as well as counts only, which is consistent with the inimitability argument in P7.

11. Boundary Conditions:

A theory is honed by declaring its inapplicability. The theory suggested is weak or fails in the following situations.

1. Strategic immateriality. In situations where AI is not central to the value proposition, capability differences are unlikely to create much value, thereby reducing the theory's predictive power.
2. Commoditized parity. When AI is provided as a uniform third-party offering to all competitors, the configuration becomes commonplace and imitable, and benefit is lost no matter the ability.
3. Skim or unreachable data. When the data specific to the firm is not exploitable, the formation mechanism cannot be anchored to data capability, as that data is not available.

4. Hyper-turbulence. In places where the technological frontier moves more rapidly than the loops of learning can keep pace, path dependence is a liability rather than an asset, and algorithmic capital might be obsolescent.

5. Severe resource constraint. In cases where the organization does not meet the minimum threshold of talent or infrastructure, there will be no integration and no higher-order capability will arise.

These circumstances restrict the scope of the theory, and, at the same time, delineate the areas where AI-based advantage is most feasible: strategically material domains, where proprietary data and algorithmic capital are exploitable, where technological change is moderate, and where non-trivial barriers to imitation exist.

12. Theoretical Contributions:

12.1. Contribution to Theory

There are three theoretical contributions in the paper; they collectively respond to the question of what a theoretical contribution has to be, that is, what constructs, what relationships, and what causal logic underlies the relationship (Whetten, 1989). First, it provides an integrative definition of organizational AI capability that addresses the plurality in the definition of the construct and differentiates it from readiness, adoption, and maturity. Second, it provides a three-level architecture that decouples resources (such as algorithmic capital), components, and emergent capability and clarifies the level confusion prevalent in the original work. Third, it defines a transformation mechanism and propositions that transform a descriptive label into an explanatory, testable theory of how algorithmic capital is converted to organizational capability.

The theory contributes to the micro-foundations of AI capability in organizations, relatedly. Instead of considering capability as a black box that is associated with performance, it details the lower-level building blocks of resources, components, and the integration activities to assemble capability. Based on the micro-foundations program (Felin et al., 2012), the theory identifies three micro-level sources of capability and how these are cross-leveled: individuals (data scientists, engineers, and domain experts who frame problems and interpret outputs), social processes (the team- and unit-level interactions where AI outputs are negotiated into decisions and routines), and structure (the engineered architecture decision rights, workflows, and governance) through which these interactions are channeled). Capability is therefore not a property held at any one level but an emergent accumulation: personal expertise is bundled together by team and unit processes and fixed by organizational structure so that what starts off as individual action becomes, through planned engineering, an organizational-level capacity. This cross-level answer to a long-standing call in the dynamic-capabilities literature to describe how higher-order capabilities are constructed from micro-level action, not that they exist.

12.2. Contribution to Management Theory

In the case of management theory, the paper presents three arguments. In theory, it transforms the vaguely defined AI capability into a higher-order, structured construct with levels, components, and a causal formation process, and it combines four established traditions resource-based, knowledge-based, dynamic-capabilities, and organizational-learning with a Business Engineering perspective of organizational redesign (Abuhaimed, 2026a). As an exercise, it re-frames the managerial challenge of obtaining AI as one of creating the organizational conditions, processes, governance, architecture, and learning routines under which algorithmic capital will be a value-creating capability. Unlike the previous literature, which considers adoption, readiness, governance, and algorithmic capital as distinct phenomena, the paper identifies the connections among them, providing management scholars with a testable theory of capabilities formation rather than another description of maturity scheme.

12.3. A Design-Theoretic Contribution: Capability as Engineered

One specific contribution concerns the means of achieving the transformation, and in this case, Business Engineering is not a marginal contribution. The majority of capability theories argue that integration is relevant but do not specify how to achieve it within the organization, treating it as a matter of managerial will. This theory incorporates Business Engineering (Abuhaimed, 2026a) as the design logic of the mechanism, making a design-theoretic assertion: organizational AI capability is not just developed but designed, i.e., purposely created as the redesign of structures, processes, decision rights, governance, and digital architecture. The contribution thereby fills the gap between the strategy literature on capabilities and the design tradition in information systems, making organizational redesign the operational pathway for the resource-to-capability transformation.

12.4. Contribution to the Research Program

In addition to its value on its own, the paper provides an unbroken continuum to a cumulative program. Previous literature explained how talent management enhances knowledge sharing and AI preparedness (Abuhaimed et al., 2024), empirically showed that the former two contribute to the adoption of AI (Abuhaimed et al., 2025), and redefined AI assets as manageable algorithmic capital (Abuhaimed, 2026b). The current theory describes how algorithmic capital becomes a higher-order organizational AI capability, placing the construct midstream between competitive advantage and program downstream constructs.

12.5. Contribution to Practice

For the managers, the central task is re-framed in the framework. It is not to obtain AI or even to stock up on algorithmic capital, but to combine it, to develop the components of capability, and, most importantly, the complementarities between them. It warns that cost without capability is investment in resources without integration, governance, and learning, and it recognizes governance, learning, and disciplined process/decision/workflow integration as the levers that transform fragile technical victories into sustainable advantage.

12.6. The Core Scientific Addition

This theory describes the process through which an organization transitions to having an AI-based organizational capability-and that capability to sustainable competitive advantage.

12.7. Limitations:

This paper has limitations as a conceptual contribution which frames its claims. It is hypothetical and untestable: the propositions are obtained analytically and are subject to empirical testing. Before its constructs can be operationalized reliably, especially its five components and the three integration sub-capabilities need to be measured. The scope conditions of Section 10 also limit the theory, and its assertions are most robust in data-rich, strategically material, moderately turbulent environments and weakest in others. Lastly, the framework favors the organizational level of explanation and places less emphasis on individual-level and ecosystem-level dynamics, which future research might have to consider.

12.8. Future Research:

The propositions are invitations to empirical work in three directions. Measurement: creating and validating scales of each component of the capability, as well as the three sub-capabilities of integration, preferably in the form of a higher-order reflective-formative construct. Modeling: predictive and formative constructs can be tested with variance-based P1-P7 structural equation modeling PLS-SEM and confirmatory tests with covariance-based SEM (CB-SEM); configurational logic (P3: the claim of complementarity) and necessity claims (P2: the claim of necessity) are well suited to fuzzy-set qualitative comparative analysis (fsQCA). Design: The compounding learning loop (P4) requires longitudinal designs that trace capability trajectories over time, whereas the cross-level logic, between individuals' routines and organizational capability, encourages multilevel analysis. Studying the boundary conditions in industries that differ in data richness, algorithmic capital intensity, and technological turbulence would further narrow down the scope of the theory.

13. Conclusion:

Algorithmic capital is becoming the property of organizations; what remains scarce is the ability to convert it into advantage. The distinction is based on organizational AI capability - a higher-order, multidimensional, dynamic capability that is created when algorithmic capital and associated resources are synthesized together via data, technical, governance, learning, and integration elements, and is replenished through learning. The fact that integration is, fundamentally, an organizational engineering: the ability to form is explicitly created when companies consciously re-engineer their structures, processes, governance, and architectures around AI, in such a way that the transformation of resource to capability is not left to chance. By defining this construct, differentiating it from similar terms, designing its layers, defining its creation, and scoping its domain, the paper seeks to provide a shared basis to the field, and this research program, in particular: a theory of how AI can become not just an ownership, but a benefit.

13.1 Theoretical Legacy:

The theory promotes a larger reconceptualization, beyond filling a particular gap. It redefines AI capability not as a set of assets that a firm builds up but as a more advanced organizational capability engineered by engineering the organization itself. According to this perspective, the question that research and practice will focus on is no longer how much AI the firm has but how the firm has been redesigned such that AI can become a capability. This transformation, between ownership and design, between asset and architecture, shifts the focus of the field towards the organizational, rather than simply the technological, principles of AI-enabled advantage. Provided the main thesis of the theory is true, then it will be the most mindful who manages to designate sustainable advantage in the AI era, not the owner of the strongest models, but the most mindful engineer of their organizations to transform algorithmic capital into capability. That suggestion--and the building, system, and design designed to validate it--is what this paper offers others to experiment with, elaborate on, and debate.

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