PERFECT EDUCATION FAIRY
Volume 4, Number 2, 2026

Artificial Intelligence as a Strategic Digital Resource: Extending the Digital Resource View Through a Layered Resource Architecture

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Abstract
Artificial intelligence (AI) has become a central element of digital transformation, yet strategic-management research still lacks a sufficiently precise explanation of when AI constitutes a strategic resource rather than a widely accessible technology. This conceptual study extends the Digital Resource View (DRV) by theorizing AI as a configured, multi-layered digital resource architecture composed of AI infrastructure, AI capability, AI-driven decision systems, and AI-orchestrated digital platforms. Following a theory-adaptation design, the article integrates resource-based theory, resource orchestration, dynamic capabilities, digital transformation, organizational AI capability, platform, and institutional perspectives. The resulting framework specifies how the four AI layers are connected and how they activate three DRV transmission mechanisms—digital value creation, digital rareness, and uncertainty-driven imitation barriers—to generate competitive advantage. Normative digital pressure is introduced as a contextual condition that shapes the conversion of AI-enabled decision systems into realized digital value. Ten propositions clarify the causal logic and make the framework empirically testable. The study contributes by distinguishing AI resource layers from AI outcomes, replacing a direct technology–performance assumption with an orchestration-based mechanism, and clarifying how configurational uniqueness and learning uncertainty can sustain advantage even when core AI technologies are widely available. The framework also identifies boundary conditions for platform dependence, institutional context, and governance capacity, thereby providing a more disciplined foundation for future empirical research on AI-enabled competitive advantage.

Keywords
Artificial intelligence; Digital Resource View; Resource orchestration; Competitive advantage; Digital value creation; AI capability; Normative digital pressure

DOI: https://doi.org/10.56442/pef.v4i2.1381

1. Introduction

Artificial intelligence (AI) is moving from isolated experimentation to the core of organizational transformation. Firms increasingly deploy AI to augment managerial judgment, automate complex processes, personalize services, accelerate innovation, and coordinate activities across organizational and ecosystem boundaries (Jarrahi, 2018; Perifanis & Kitsios, 2023; Trocin et al., 2021). The strategic relevance of AI therefore extends beyond technical performance. It concerns how organizations assemble data, computing infrastructure, models, human expertise, governance routines, and ecosystem relationships into configurations that can alter value-creation pathways (Haefner et al., 2023; Mikalef & Gupta, 2021; Sjödin et al., 2021). This broader view is consistent with digital-transformation research, which conceptualizes transformation as an organizational process in which digital technologies trigger strategic responses and changes in value creation rather than as the simple adoption of technology (Vial, 2019).

Resource-based theory (RBT) provides an intuitive starting point for examining the strategic consequences of AI because it links performance heterogeneity to differences in firm resources and capabilities (Barney, 2001; Barney et al., 2021). Yet the application of traditional resource logic to AI is not straightforward. Many foundational AI components—cloud services, foundation models, open-source libraries, standardized APIs, and external data services—can be acquired by multiple competitors. Their availability weakens any assumption that technology ownership alone is necessarily rare or inimitable. In addition, AI assets can be recombined rapidly, improve through iterative learning, and become embedded in interorganizational platforms. These characteristics shift analytical attention from resource possession toward configuration, orchestration, learning, and contextual deployment (Amit & Han, 2017; Cuthbertson & Furseth, 2022; Helfat et al., 2023).

This tension reveals a theoretical gap. A large part of the AI–business-value literature explains how firms build AI capability or derive performance benefits from AI, but it often leaves under-specified the resource architecture that connects foundational digital assets to organization-level routines and ecosystem-level advantage (Mikalef & Gupta, 2021; Perifanis & Kitsios, 2023). Conversely, resource-based research increasingly acknowledges digitization and AI as new strategic contexts, but it does not by itself specify the layered organizational configuration through which AI becomes strategically consequential (Helfat et al., 2023). A stronger account therefore requires a theory of how heterogeneous AI-related elements are progressively configured and how their effects are transmitted to competitive outcomes.

The Digital Resource View (DRV) offers a useful starting point for this purpose. DRV has been proposed as an extension of resource-based reasoning for digital environments, emphasizing scalability, recombinability, embeddedness, digital value creation, digital rareness, uncertainty-driven imitation barriers, and normative digital pressure (Adamu, 2025a, 2025b). Importantly, DRV should be treated as an emerging theoretical extension rather than as a fully established substitute for RBT. Its value lies in directing attention toward mechanisms that are particularly salient when resources are digitally replicable but strategically heterogeneous in their configuration. The present article strengthens that emerging logic by grounding it more explicitly in established resource orchestration, dynamic capabilities, digital transformation, and organizational AI research (Sirmon et al., 2011; Teece, 2007).

Accordingly, this article asks: How can AI be conceptualized as a configured strategic digital resource within DRV, and through which mechanisms can a layered AI architecture contribute to competitive advantage? To answer this question, the study develops a four-layer architecture—AI infrastructure, AI capability, AI-driven decision systems, and AI-orchestrated digital platforms—and links these layers to digital value creation, digital rareness, and uncertainty-driven imitation barriers. Normative digital pressure is modeled as a contextual condition affecting value realization. The article makes three contributions. First, it distinguishes resources, capabilities, embedded decision routines, and ecosystem orchestration rather than treating AI as a single undifferentiated resource. Second, it replaces a direct AI-adoption-to-performance argument with explicit transmission mechanisms. Third, it refines the institutional component of DRV by separating normative expectations from coercive regulation and by specifying boundary conditions under which normative pressure can strengthen rather than suppress AI-enabled value creation.

2. Conceptual Method

This study is a conceptual theory-adaptation article. Conceptual research is appropriate when the objective is to refine the assumptions, constructs, and causal logic of an existing theoretical perspective rather than to estimate empirical relationships. Following

Jaakkola (2020), the analytical task is therefore to make explicit (1) the theoretical problem, (2) the theories used as inputs, (3) the logic through which those inputs are combined, and (4) the resulting conceptual contribution. The present article does not claim to be a systematic literature review and does not infer population-level evidence from a bibliographic sample. Instead, it uses theory-driven source selection to develop and discipline the DRV–AI argument.

The theoretical base comprises five complementary streams. First, resource-based theory provides the core logic of value, heterogeneity, and value appropriation (Barney, 2001; Barney et al., 2021). Second, resource orchestration and dynamic capabilities explain why resources must be structured, bundled, leveraged, and reconfigured rather than merely owned (Sirmon et al., 2011; Teece, 2007). Third, digital-transformation and digital-resource research explain the scalability, recombinability, and continuous redevelopment of digital assets (Amit & Han, 2017; Cuthbertson & Furseth, 2022; Vial, 2019). Fourth, organizational AI research identifies the technical and managerial components needed to build and scale AI capability and embed it in business processes (Haefner et al., 2023; Mikalef & Gupta, 2021; Sjödin et al., 2021). Fifth, platform and institutional perspectives clarify ecosystem embeddedness and the legitimacy conditions surrounding digital deployment (Bennich, 2024; Rai et al., 2019; Trier et al., 2023). DRV provides the focal theory to be extended (Adamu, 2025a, 2025b).

The analytical procedure involved four steps. First, the assumptions of RBT and DRV were compared to identify where AI challenges ownership-centered explanations. Second, AI-related constructs were separated according to their strategic function: foundational assets, organizational capability, embedded decision routines, and ecosystem orchestration. Third, causal mechanisms were specified by asking what must change between one layer and the next and why that change should affect value, rareness, or imitation. Fourth, propositions were derived and checked for construct redundancy, causal ordering, and boundary conditions. This procedure yields a framework that is intended to be testable rather than merely descriptive.

3. Theoretical Foundations

3.1 Resource-Based Theory, Orchestration, and the Digital Challenge

RBT explains performance heterogeneity by focusing on firm-specific resources and capabilities that create value and allow firms to appropriate part of that value (Barney, 2001; Barney et al., 2021). Traditional formulations emphasize resource heterogeneity and imperfect mobility, while later work has clarified that RBT is not inherently static and can accommodate managerial action, uncertainty, and resource recombination. Resource orchestration makes this point explicit by emphasizing managerial processes that structure resource portfolios, bundle resources into capabilities, and leverage those capabilities in competitive settings (Sirmon et al., 2011). Dynamic capabilities similarly explain how firms sense opportunities, seize them, and reconfigure asset bases under conditions of rapid technological change (Teece, 2007).

These developments are important because a simple contrast between a 'static' RBT and a 'dynamic' digital world would be theoretically inaccurate. The limitation is more specific: an ownership-centered reading of resource advantage becomes less informative when important digital technologies are broadly accessible and when strategic heterogeneity emerges primarily from how they are combined, trained, governed, embedded, and continuously redeployed. Digitally enabled value creation increasingly depends on resource configurations that cross organizational boundaries and mobilize assets controlled by multiple actors (Amit & Han, 2017). Digital services also require continual redevelopment, making innovation capability and complementary resources central to sustaining advantage (Cuthbertson & Furseth, 2022).

AI intensifies these issues. Two firms can acquire similar cloud capacity or access similar models but obtain markedly different outcomes because their data quality, process integration, managerial expertise, governance, human–AI coordination, and ecosystem positioning differ. Organizational AI capability is therefore an emergent bundle rather than a single technology (Mikalef & Gupta, 2021). Likewise, scaling AI requires socio-technical transition from proof of concept to production and, in some settings, to platformization (Haefner et al., 2023). These observations support a configurational extension rather than the rejection of resource-based logic.

3.2 Digital Resource View: Constructs and Clarifications

DRV is used here as an emerging extension of resource-based reasoning designed to foreground properties that are unusually important in digital settings (Adamu, 2025a, 2025b). Three properties are central. Scalability allows a digital resource to be deployed across users, processes, and locations at relatively low marginal cost. Recombinability allows data, software, algorithms, interfaces, and organizational routines to be reassembled into new services and operating models. Embeddedness means that the strategic meaning of a digital resource depends on its location within socio-technical and interorganizational systems. These properties imply that digital strategic value is frequently configurational rather than attributable to a standalone asset.

The present study retains four DRV mechanisms but clarifies their roles. Digital value creation denotes improvements in customer value, productivity, innovation, coordination, or strategic responsiveness that arise from the configured use of digital resources. Digital rareness refers not to the scarcity of a generic technology but to the relative scarcity of a firm-specific configuration—for example, a distinctive combination of proprietary data, process knowledge, model adaptation, user relationships, and ecosystem position. Uncertainty-driven imitation barriers refer to barriers that arise because competitors cannot reliably infer the causal configuration producing observed performance, especially when algorithms, data, routines, and human expertise co-evolve. Normative digital pressure refers specifically to professional norms, industry standards, and societal expectations regarding legitimate digital conduct. Formal legal mandates are conceptually closer to coercive pressure and should not be collapsed into the normative construct (Bennich, 2024).

This clarification matters because the original DRV–AI logic can otherwise become tautological: if any successful digital configuration is labeled rare and inimitable after the fact, the theory cannot be falsified. The framework below therefore assigns mechanisms to specific antecedent layers, specifies observable dimensions, and identifies conditions under which the predicted relationships may not hold.

Table 1. Core constructs in the proposed DRV–AI framework

Construct	Definition	Indicative dimensions
AI infrastructure	Foundational computing, data, storage, integration, API, and security assets that enable AI development and deployment.	Scalability, interoperability, data readiness
AI capability	Organizational ability to develop, integrate, retrain, monitor, and govern AI by combining technical, human, and managerial resources.	Model development, data competence, integration routines, governance
AI-driven decision systems	Socio-technical arrangements embedding AI outputs into recurring managerial and operational decisions.	Workflow integration, decision rights, automation/augmentation, human oversight

Construct	Definition	Indicative dimensions
AI-orchestrated digital platforms	Ecosystem-level digital arrangements using AI to coordinate interactions, data flows, and resource allocation across actors.	Ecosystem integration, interaction data, network effects, algorithmic coordination
Digital value creation	Value generated through improved productivity, innovation, personalization, responsiveness, or coordination from configured digital resources.	Operational improvement, innovation outcomes, stakeholder value
Digital rareness	Relative scarcity of a firm-specific digital configuration rather than scarcity of generic technology.	Unique data/configuration, ecosystem position, complementary routines
Uncertainty-driven imitation barriers	Difficulty rivals face in inferring and replicating a changing data–model–process configuration.	Causal ambiguity, path dependence, learning opacity, configuration volatility
Normative digital pressure	Professional, industry, and societal expectations concerning legitimate and responsible digital conduct.	Professional norms, industry standards, stakeholder expectations

3.3 Artificial Intelligence as a Layered Strategic Digital Resource

3.3.1 AI Infrastructure: Foundational Digital Assets

AI infrastructure comprises the technical assets that make model development and deployment possible: computing capacity, cloud architecture, data storage, data pipelines, APIs, model-development environments, cybersecurity controls, and integration interfaces. Infrastructure is strategically relevant because it determines data accessibility, scalability, interoperability, and the speed with which models can move from experimentation into production. However, infrastructure alone is unlikely to produce durable advantage when comparable services can be purchased by competitors. Its primary strategic role is enabling the development of higher-order AI capability.

This distinction between an asset base and a capability is essential. A firm may own or rent extensive computing resources while lacking the routines required to curate data, select models, retrain systems, monitor drift, integrate outputs, or govern risks. Resource orchestration therefore predicts that infrastructure generates strategic effects only when it is bundled with skills and routines (Sirmon et al., 2011). Similarly, evidence on AI scaling shows that the transition from proof of concept to production depends on socio-technical components extending beyond raw computing capacity (Haefner et al., 2023).

Proposition 1 (P1). Greater scalability, interoperability, and data readiness of AI infrastructure positively influence the development of organizational AI capability.

3.3.2 AI Capability: Development and Integration Capacity

AI capability is the firm's ability to mobilize technological, human, and organizational resources to develop, integrate, retrain, monitor, and govern AI applications. This definition is consistent with work that conceptualizes AI capability as a multidimensional organizational construct rather than a technology stock (Mikalef & Gupta, 2021). It includes technical skills, data-management competence, model-development routines, domain expertise, governance, and the managerial ability to coordinate AI with business objectives.

A capability becomes strategically meaningful when it is repeatedly exercised and embedded in organizational routines. Firms that can build models but cannot integrate them into workflows remain trapped in experimentation. Conversely, firms that combine data pipelines, algorithm development, and organization-wide accessibility can scale AI into operating processes and business-model innovation (Sjödin et al., 2021).

Proposition 2 (P2). Higher organizational AI capability positively influences the embedding of AI into AI-driven decision systems.

3.3.3 AI-Driven Decision Systems: Cognitive and Operational Embedding

AI-driven decision systems are socio-technical arrangements in which AI outputs are embedded in recurring managerial or operational decisions. Examples include demand forecasting, credit assessment, predictive maintenance, dynamic pricing, recommendation, anomaly detection, and resource allocation. The key distinction is that a model becomes part of a decision system only when its outputs are connected to decision rights, workflows, accountability, and human judgment. Human–AI complementarity is especially important where decisions involve uncertainty, complexity, and equivocality (Jarrahi, 2018).

This layer is where AI capability begins to create realized organizational value. AI may improve prediction, accelerate information processing, automate routine choices, or augment managerial attention, but these benefits depend on process redesign and actual use. AI affordances generate innovation only when organizations actualize them through actors, goals, and tasks (Trocin et al., 2021). Thus, the decision-system layer connects technical capability to operational and strategic outcomes.

In ecosystem-dependent business models, mature internal decision systems can also become the basis for platform-level orchestration. Standardized data flows, algorithmic interfaces, and automated coordination can be extended to customers, suppliers, and partners. This progression should not be interpreted as universal: many firms can realize substantial AI value without operating a platform. The proposed relationship is therefore bounded to contexts in which ecosystem coordination is strategically important.

Proposition 3 (P3). In ecosystem-dependent contexts, greater maturity of AI-driven decision systems positively influences the development of AI-orchestrated digital platforms.

Proposition 4 (P4). Greater maturity of AI-driven decision systems positively influences digital value creation.

3.3.4 AI-Orchestrated Digital Platforms: Ecosystem-Level Configuration

AI-orchestrated digital platforms extend algorithmic coordination beyond internal organizational processes. They connect multiple actors through shared digital interfaces while using AI to match participants, prioritize information, personalize interactions, allocate resources, detect risk, or optimize ecosystem activity. Digital platforms are increasingly hybrid arrangements in which human and AI agency interact (Rai et al., 2019). In industrial contexts, AI-enabled ecosystem integration can support scalable business-model innovation and new forms of value co-creation (Sjödin et al., 2021, 2023).

The strategic importance of this layer lies less in the platform software itself than in accumulated configuration. Repeated interactions generate proprietary data, feedback loops, switching relationships, domain-specific model adaptations, and interdependencies among ecosystem participants. These elements can create configurations that are uncommon even when competitors have access to similar generic AI models. In DRV terms, the platform layer is therefore particularly relevant to digital rareness.

AI-orchestrated platforms may also increase imitation uncertainty. Competitors can often observe a platform's interface but not the full historical process through which datasets, partner routines, model parameters, governance choices, and user behaviors became mutually reinforcing. This opacity produces causal ambiguity and path dependence rather than absolute technological secrecy.

Proposition 5 (P5). Greater development of AI-orchestrated digital platforms positively influences digital rareness through firm-specific data, interaction, and ecosystem configurations.

Proposition 6 (P6). Greater development of AI-orchestrated digital platforms positively influences uncertainty-driven imitation barriers.

4. DRV Transmission Mechanisms and Competitive Advantage

Digital value creation is the first transmission mechanism. The argument is not that AI automatically creates value, but that AI-driven decision systems can improve prediction, automation, personalization, coordination, and innovation when embedded in appropriate workflows (Perifanis & Kitsios, 2023). Value creation should therefore be measured independently from the existence of AI capability. This separation avoids conflating a resource with its outcome.

Digital rareness is the second mechanism. In AI-intensive competition, rareness is often configurational rather than technological. A generic model or cloud service may be common, while the combination of proprietary data, domain knowledge, retraining routines, customer relationships, and ecosystem access remains difficult to reproduce. This logic is consistent with digitally enabled resource-configuration research, which emphasizes novel combinations rather than isolated ownership (Amit & Han, 2017).

Uncertainty-driven imitation barriers are the third mechanism. They arise when competitors cannot determine which combination of data, model, process, human expertise, organizational history, and ecosystem interaction causes superior outcomes. AI can deepen causal ambiguity because models change through retraining, data distributions evolve, and organizational learning modifies how outputs are used. Yet uncertainty is not automatically protective. If a firm's advantage is based only on an easily observable model or a standardized service, imitation may be rapid. The proposed barrier therefore depends on historical learning and socio-technical embeddedness.

These mechanisms have different strategic roles but converge on competitive advantage. Value creation is necessary because a rare and opaque configuration that produces no stakeholder value cannot support superior performance. Rareness affects the distribution of value by limiting the number of competitors with equivalent configurations. Imitation barriers affect persistence by slowing the erosion of that advantage. This formulation is compatible with value-creation-centered interpretations of resource-based theory (Barney et al., 2021).

Proposition 7 (P7). Digital value creation positively influences competitive advantage.

Proposition 8 (P8). Digital rareness positively influences competitive advantage.

Proposition 9 (P9). Uncertainty-driven imitation barriers positively influence the persistence of competitive advantage.

5. Normative Digital Pressure as a Contextual Moderator

Organizations deploy AI within institutional environments that shape legitimacy. Normative digital pressure arises from professional norms, industry standards, customer expectations, investor expectations, and broader societal beliefs about responsible digital conduct. This construct must be distinguished from coercive regulatory pressure. Institutional research on digitalization shows that normative and mimetic processes can legitimize digital practices, whereas formal regulation operates through different mechanisms (Bennich, 2024). Research on digital responsibility likewise emphasizes that responsible digitalization is a multilevel organizational challenge involving governance, accountability, and stakeholder expectations (Trier et al., 2023).

Normative pressure can strengthen value realization when it gives organizations clearer expectations for trustworthy AI, encourages governance routines, and increases stakeholder acceptance. However, a universally positive effect should not be assumed. Ambiguous, conflicting, or excessive expectations can increase compliance costs, delay experimentation, or encourage symbolic adoption. The framework therefore proposes a conditional moderation rather than a mechanically positive institutional effect.

Proposition 10 (P10). Normative digital pressure conditions the positive relationship between AI-driven decision systems and digital value creation; the relationship is expected to be stronger when normative expectations are clear, legitimate, and organizationally internalized.

6. Integrated Conceptual Framework

Figure 1 integrates the propositions into a single causal architecture. The upper portion represents the progressive configuration of AI resources from infrastructure to capability, embedded decision systems, and, where strategically relevant, ecosystem-level platforms. The lower portion separates the mechanisms through which these layers affect competitive advantage. Decision systems primarily activate digital value creation; platform configurations primarily contribute to digital rareness and uncertainty-driven imitation barriers. This does not imply that the mechanisms are mutually exclusive. Rather, the mapping identifies the dominant theoretical channel associated with each layer and thereby improves testability.

The framework also resolves an ambiguity in the original vertically aligned model. AI-orchestrated platforms are not a necessary stage for every organization. A bank, hospital, manufacturer, or public agency may achieve substantial AI-enabled value through internal decision systems without becoming a multi-sided platform. Accordingly, P3 is explicitly bounded to ecosystem-dependent contexts. This change preserves the layered architecture while avoiding the stronger—and empirically implausible—claim that all strategic AI development must culminate in platform orchestration.

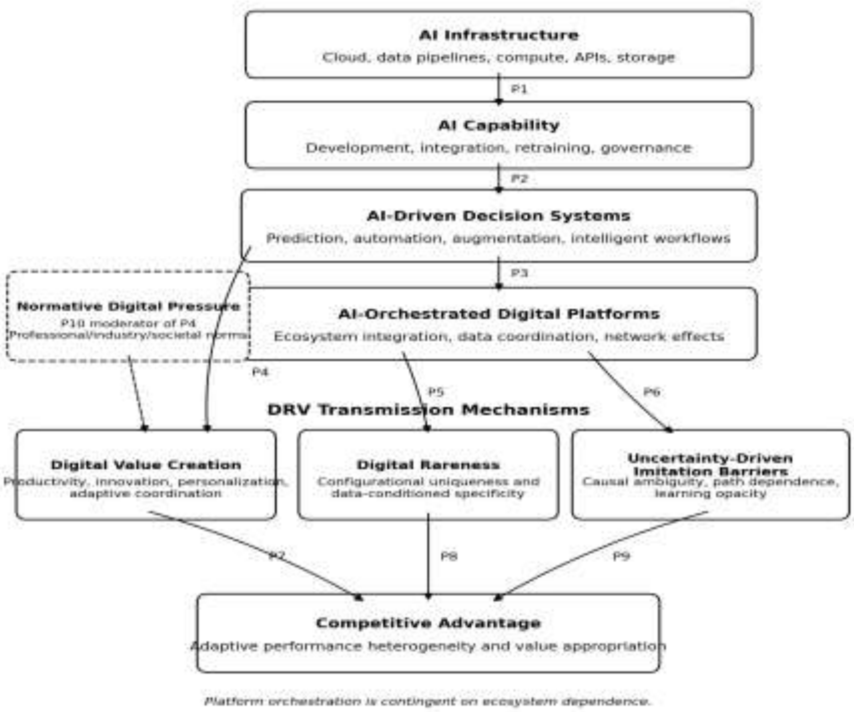

Figure 1. Layered DRV–AI conceptual framework and proposed relationships.
Note. The platform layer is contingent on ecosystem dependence; normative digital pressure is distinguished from coercive regulatory pressure.

7. Discussion

The framework advances the strategic interpretation of AI in several ways. Most importantly, it rejects the binary question of whether AI itself is valuable, rare, or inimitable. That question is poorly posed when core AI technologies are increasingly accessible. The relevant unit of analysis is the configured resource architecture. Infrastructure provides an enabling base; capability represents the organization's capacity to mobilize that base; decision systems embed AI in recurrent choices; and platforms extend coordination across ecosystem actors. Competitive advantage therefore depends on how these elements are combined and renewed, not on AI ownership in isolation.

This layered logic also helps explain heterogeneous returns to AI investment. Firms may invest heavily in infrastructure but fail to build integration capability. Others may develop technically sophisticated models that remain disconnected from decision rights and workflows. Still others may embed AI internally but lack the partner relationships, governance, or network scale required for ecosystem orchestration. These failure points are theoretically different and should not be collapsed into a generic construct of 'AI adoption.' The framework therefore creates a more precise basis for diagnosing where value conversion breaks down.

A second contribution concerns the meaning of rareness in digital contexts. When software and models are replicable, rareness can migrate from the focal technology to the surrounding configuration. Proprietary data are one source, but not the only one. Process knowledge, user interaction histories, integration architecture, model-governance routines, complementary human expertise, and ecosystem position can jointly generate a configuration that is relatively uncommon. Digital rareness is thus relational and path dependent rather than absolute.

A third contribution concerns imitation. Traditional RBT already recognizes causal ambiguity and path dependence, so uncertainty-driven imitation barriers should not be presented as wholly replacing established theory. The extension lies in specifying why AI-intensive configurations can amplify and continuously reshape these barriers: data distributions change, models are retrained, interfaces are modified, and human practices adapt. The object to be imitated is therefore moving. Sustained advantage, if it occurs, depends on continued learning and reconfiguration rather than on permanent protection of a fixed asset.

Finally, the institutional component adds a legitimacy dimension to AI strategy. Responsible deployment, explainability, data governance, professional standards, and stakeholder expectations influence whether technically effective AI systems can be accepted and scaled. Yet the construct must remain theoretically disciplined. Normative expectations are not equivalent to legal requirements, and pressure is not inherently beneficial. The effect depends on clarity, internalization, and organizational governance capacity. This refinement makes the moderator more defensible and empirically measurable.

8. Theoretical Contributions

First, the study extends DRV by specifying an explicit architecture through which digital resources become strategically consequential. This improves construct clarity because infrastructure, capability, decision systems, and platforms are positioned at different analytical levels. Future studies can therefore test whether treating AI as a single reflective construct obscures important causal differences.

Second, the study links DRV to established resource orchestration and dynamic-capabilities reasoning. The extension is therefore not based on the claim that RBT is obsolete. Instead, it argues that AI makes orchestration especially visible because strategic value frequently resides in integration and reconfiguration. This positioning reduces theoretical overstatement and makes DRV more cumulative with mainstream strategic-management theory.

Third, the framework reconceptualizes digital rareness and imitation barriers in testable terms. Digital rareness can be operationalized through uniqueness of data access, integration patterns, domain-specific model adaptation, ecosystem relationships, and complementary routines. Uncertainty-driven imitation barriers can be operationalized through causal ambiguity, learning history, opacity of data–model–process interactions, and speed of configuration change.

Fourth, the model offers a bridge between strategic-management and information-systems research. AI capability studies identify the resources required to build organizational AI competence, while digital-platform and transformation studies explain how such competence is scaled and embedded. DRV provides a strategic mechanism linking these literatures to competitive outcomes.

Table 2. Summary of theoretical extensions

Theoretical domain	Conventional emphasis	DRV–AI extension	Contribution
Resource logic	Resource ownership / VRIN emphasis	Configured, layered AI architecture	Moves the unit of analysis from AI ownership to resource orchestration
Value creation	Potentially direct resource–performance link	Mediated through digital value creation	Separates AI resources from realized value outcomes
Rareness	Scarcity of a resource or capability	Configurational and data-conditioned uniqueness	Explains rareness when generic AI is widely accessible
Imitation barriers	Causal ambiguity, path dependence, social complexity	Continuously evolving uncertainty in data–model–process configurations	Extends persistence logic to moving digital configurations
Institutional context	Often peripheral to resource arguments	Normative digital pressure as a contextual condition	Links AI value realization to legitimacy and responsible deployment
AI conceptualization	Technology or aggregate capability	Infrastructure → capability → decision systems → conditional platform orchestration	Clarifies levels and testable causal ordering

9. Managerial Implications

For managers, the framework implies that AI investment should be evaluated as a portfolio of interdependent layers rather than as a sequence of technology purchases. Infrastructure spending should be justified by its contribution to capability development. Capability initiatives should be assessed by their ability to change recurring decisions and workflows. Platform investments should be pursued only when ecosystem coordination, data interaction, and network effects are central to the business model.

The model also suggests that firms should not search for advantage exclusively in proprietary algorithms. As frontier models become more accessible, advantage may depend more on proprietary context: high-quality data, process redesign, integration architecture, decision rights, customer relationships, feedback loops, and governance routines. Managers should therefore track configuration-specific learning and protect the complementary assets that make AI useful.

Governance should be treated as an enabling capability rather than merely a compliance function. Clear accountability, model monitoring, data stewardship, and stakeholder communication can increase trust and make AI outputs more usable. At the same time, governance systems should distinguish normative expectations from mandatory legal constraints because the two create different strategic responses.

10. Boundary Conditions and Future Research

The framework has several boundary conditions. First, it applies primarily to organizations in which AI is strategically relevant and sufficiently integrated with digital infrastructure. It is less applicable to firms using AI only for peripheral or transactional tasks. Second, the platform layer is contingent rather than universal. Organizations whose value creation is predominantly internal may stop at the decision-system layer. Third, the moderator is normative digital pressure, not regulation in general; coercive legal requirements require separate theorization. Fourth, the model assumes that organizations retain meaningful discretion over resource configuration. In settings where models, data, workflows, and governance are almost entirely standardized by an external provider, firm-level heterogeneity may be limited.

Future empirical research can test the framework using multi-level and longitudinal designs. One research stream should validate the four AI layers as distinct constructs and examine whether a formative or hierarchical measurement model best represents their relationships. A second stream should test the three transmission mechanisms separately rather than using a single generic performance mediator. A third should investigate temporal dynamics: for example, whether digital value creation emerges earlier than digital rareness and whether imitation barriers strengthen only after cumulative learning. A fourth should examine context, including emerging economies, regulated sectors, business-to-business ecosystems, and small and medium-sized firms.

Researchers should also investigate alternative causal structures. AI capability may directly support platform orchestration without an intermediate decision-system stage; platforms may feed new data back into capability development; and competitive advantage may fund further infrastructure investment. Longitudinal designs are therefore preferable to cross-sectional tests if the objective is to capture recursive learning. The current framework presents the dominant directional logic for theory testing, not an assertion that organizational AI development is perfectly linear.

11. Conclusion

This article reconceptualizes AI as a layered strategic digital resource architecture within an extended Digital Resource View. The central claim is not that AI technology is inherently rare or inimitable. Rather, competitive advantage can emerge when firms configure AI infrastructure into organizational capability, embed that capability in decision systems, and—where ecosystem dependence makes it relevant—extend those systems into AI-orchestrated platforms. These layers influence competitive outcomes through digital value creation, digital rareness, and uncertainty-driven imitation barriers.

The revised framework is deliberately conditional. Infrastructure is an enabler rather than a direct source of advantage; platform orchestration is not necessary for every firm; normative digital pressure is distinct from coercive regulation; and institutional pressure does not automatically create value. By making these limits explicit, the framework becomes more falsifiable and better aligned with established strategic-management and information-systems scholarship. Future empirical work can now examine not simply whether AI adoption improves performance, but which configurations produce value, under what institutional conditions, and how those configurations become difficult for competitors to reproduce over time.

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