

ORIGINAL RESEARCH

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Digital Firms as Learning Systems: Continuous Organizational Knowledge Development Through Data Interaction and Market Feedback

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Abstract

Digital firms increasingly operate as adaptive learning systems in which organizational knowledge evolves continuously through real-time data interactions and market feedback. Traditional organizational learning theories, developed in pre-digital contexts, fail to capture the velocity, volume, and interconnectedness of knowledge creation in platform-based and data-intensive environments. This theory-development article integrates insights from peer-reviewed studies on big data analytics, dynamic capabilities, digital transformation, and machine-augmented learning to reconceptualize digital firms as self-reinforcing learning systems. We propose that data streams serve as raw material for insight generation, while market feedback closes iterative loops that update organizational memory and renew capabilities. A conceptual model illustrates the continuous cycle of data ingestion, analytics-driven interpretation, strategic action, feedback reception, and knowledge accumulation. Six theoretical propositions explicate the causal mechanisms linking data interaction to capability development, feedback loops to adaptive decision systems, and analytics to the formation of long-term organizational memory. The framework advances management theory by shifting focus from episodic learning to perpetual, data-market co-evolution, offering scholars and executives a lens for understanding competitive advantage in volatile digital ecosystems. By foregrounding learning cycles over static resources, the article highlights how digital firms achieve sustained adaptation through embedded feedback architectures.

Keywords Organizational learning, Dynamic capabilities, Digital firms, Data-driven knowledge development, Market feedback loops, Continuous adaptation

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Introduction

The proliferation of digital technologies has fundamentally reshaped the competitive landscape, elevating data interaction and market feedback to central drivers of organizational survival and growth [1–5]. Digital firms—ranging from platform ecosystems to analytics-intensive service providers—no longer rely solely on periodic strategic reviews or internal knowledge repositories. Instead, they operate as living learning systems that ingest

continuous streams of user-generated data, interpret market signals in real time, and translate insights into iterative actions that refine both operations and strategy [1, 2]. This shift demands a new theoretical lens capable of explaining how knowledge accumulates not through discrete projects but through perpetual cycles of data interaction and feedback.

Conventional organizational learning models, rooted in experiential and cognitive perspectives developed for

industrial-era firms, emphasize bounded rationality, routine-based adaptation, and infrequent environmental scanning. Such frameworks overlook the defining features of digital environments: hyper-connectivity, algorithmic decision support, and instantaneous market responses [4, 6]. In digital contexts, learning becomes embedded in the firm's technical architecture, where machine learning algorithms and analytics platforms continuously process petabytes of interaction data to generate actionable knowledge [7–10]. Market feedback, once delayed and filtered through surveys or sales reports, now arrives as granular, real-time signals—clicks, ratings, dwell times, and transaction patterns—that trigger immediate capability adjustments [3, 9].

This evolution is not merely technological; it is organizational. Digital firms develop dynamic capabilities specifically attuned to data velocity and feedback intensity, enabling them to sense opportunities, seize them through rapid experimentation, and reconfigure resources faster than traditional competitors [1, 3]. Yet the literature remains fragmented. While separate streams examine big data analytics capabilities and performance [1, 2, 10], dynamic capabilities in digital transformation [3, 9], artificial intelligence's substitution for human decision-making, and organizational learning in Industry 4.0 settings [11–14], few studies integrate these elements into a unified theory of continuous knowledge development. Existing work acknowledges the importance of learning but stops short of theorizing the closed-loop architecture through which data and feedback co-evolve into organizational memory and strategic renewal [11, 15–23].

The present article addresses this theoretical gap by developing a conceptual framework that positions digital firms as learning systems. We argue that continuous organizational knowledge development arises from the interplay of three core processes: (1) data interaction as the primary input for insight generation, (2) market feedback as the evaluative and corrective mechanism, and (3) iterative learning cycles that accumulate and refine organizational memory over time. This perspective extends prior research by demonstrating how digital architectures transform episodic learning into perpetual co-evolution between the firm and its environment [4, 7, 8].

Our contribution is threefold. First, we synthesize disparate literatures on data analytics, dynamic capabilities, and digital transformation to reveal an overarching learning-system logic [2, 3, 11]. Second, we introduce a process-

oriented model that foregrounds feedback loops and knowledge accumulation, moving beyond capability lists to explain causal mechanisms [9, 24–26]. Third, we advance six propositions that specify testable relationships between data interaction, feedback intensity, learning cycles, and adaptive outcomes. These propositions provide scholars with precise constructs for future empirical work while offering managers a blueprint for designing learning-oriented digital architectures [10, 15, 20].

The remainder of the article proceeds as follows. The next section synthesizes theoretical foundations and the extant literature. We then present the theory development section, including a conceptual model and propositions. By reconceptualizing digital firms as learning systems, this article offers a timely framework for understanding how data and market feedback drive continuous knowledge development in the digital age.

Theoretical Foundations and Literature Synthesis

Digital organizational learning

Organizational learning theory has long emphasized the conversion of experience into knowledge through interpretation, integration, and institutionalization [23, 24]. In digital firms, however, learning is no longer confined to human actors or periodic routines. Instead, it occurs through socio-technical systems that continuously capture, process, and act upon data generated by user interactions and market movements [11, 13, 22]. Studies of Industry 4.0 adoption demonstrate that manufacturers develop distinct learning paths when big data analytics and connected devices become embedded in operations [12, 13]. Similarly, architectural and professional service firms illustrate how situated digital practices reshape collective learning trajectories [8]. These works collectively signal a shift from episodic to continuous learning, yet they stop short of theorizing the feedback mechanisms that sustain knowledge development across cycles [7, 11].

Feedback loops and adaptation

Digital transformation literature highlights the centrality of feedback in capability renewal. Dynamic capabilities in digital contexts are not static endowments but emerge and evolve through repeated sensing–seizing–reconfiguring cycles fueled by market signals [3, 9, 26]. One conceptualization positions digital transformation as an

ongoing process of strategic renewal [3] in which firms build sensing capabilities via data platforms. Another line of inquiry further emphasizes that feedback from platform ecosystems enables rapid experimentation and adaptation [4, 5]. In high-velocity environments, these loops compress the time between action and outcome evaluation [19], allowing firms to update mental models and resource configurations in near real time [20]. The result is a virtuous cycle in which market feedback not only corrects deviations but also actively shapes future data-collection priorities [14, 27, 28].

Knowledge accumulation in data-rich environments

Big data analytics capabilities serve as the engine of knowledge creation. Empirical and conceptual studies show that firms with mature analytics functions convert raw data into organizational knowledge that enhances innovation and performance [1, 2, 10]. One investigation demonstrates that analytics capabilities influence innovation indirectly through dynamic capabilities [2], while another establishes organizational learning as a mediator between analytics and performance [10]. Crucially, knowledge accumulation in digital firms is not linear; it is recursive. Data interaction generates insights that inform actions [17], whose outcomes produce new data that refines existing knowledge stocks [28]. Machine learning further augments this process by enabling pattern recognition at scales beyond human cognition [14], effectively decentralizing learning within platform ecosystems [22].

Analytics-driven learning systems

The integration of artificial intelligence and analytics transforms organizational learning from a human-centric to a hybrid approach. One stream of research explores how machine learning substitutes for human judgment [22], raising questions about the locus of learning. Another argues that decentralized platform structures facilitate data-driven learning by distributing decision rights across human and algorithmic agents [14]. Complementary research on digital investments shows that targeted technology spending enhances both learning processes and performance outcomes [20]. Together, these streams indicate that analytics do not merely support learning; they constitute a new learning architecture [1] in which knowledge development becomes an always-on, system-level phenomenon [10, 28].

Gaps and synthesis

Despite these advances, the literature lacks an integrative model that explains how data interaction and market feedback jointly produce continuous knowledge development. Studies remain siloed across analytics capabilities [1, 2], dynamic capabilities [3, 9, 26], AI-augmented learning [14, 22], and digital transformation [4–6]. Moreover, most frameworks treat learning as an outcome rather than a core operating logic [11, 23]. By synthesizing these bodies of work, we derive a unified theory of digital firms as learning systems in which knowledge co-evolves with data and market signals through iterative cycles. This synthesis sets the stage for the theory development that follows.

Table 1 clarifies the manuscript's core theoretical move by distinguishing continuous digital learning systems from episodic learning models across inputs, mechanisms, memory structures, and sources of competitive advantage.

Table 1. Structural contrasts between episodic organizational learning and continuous digital learning systems

Dimension	Episodic organizational learning	Continuous digital learning systems	Thim
Primary trigger of learning	Periodic reviews, projects, crises, and post hoc evaluation	Always-on data interaction and real-time market sensing	Lea fro ade enc s o
Dominant knowledge input	Human experience, reports, and bounded observation	High-volume, high-velocity, and high-variety digital traces	Data t m orga kn fo
Core interpretive mechanism	Managerial deliberation and retrospective analysis	Analytics-enabled hybrid human–machine interpretation	Kr ge b soci ra pure

Speed of learning cycle	Intermittent and slow	Near-real-time and recursive	Facilitates continuous response and feedback	Strategic advantage source	Superior resources, routines, or managerial judgment	Superior learning architecture and compounding returns to knowledge accumulation	Continuous competitive advantage
Role of feedback	Delayed, aggregated, and often weakly connected to action	Immediate, granular, behavior-based, and tightly coupled to action outcomes	Facilitates behavioral change and learning	Failure mode	Strategic rigidity, delayed response, and weak environmental fit	Data overload, loop breakage, biased models, or incomplete memory updating	Performance degradation and learning stagnation
Location of learning	Individuals, teams, routines, and formal repositories	Distributed across platforms, algorithms, dashboards, teams, and digital memory systems	Learning is embedded in organizational architecture	Continuous Learning Architectures: Data Interaction, Market Feedback, and Iterative Knowledge Co-Evolution in Digital Firms Building on the synthesized foundations, we develop a process theory of digital firms as learning systems. This perspective fundamentally reimagines organizational epistemology in the digital age. Central to this theory is the recognition that organizational knowledge is not stored in static repositories—such as formal documents or legacy databases—but emerges and evolves through a continuous architecture comprising five interlocking elements: data interaction, insight generation, action, feedback reception, and memory updating. This architecture is self-reinforcing; each completed cycle does not merely add to a stock of knowledge but augments the firm's dynamic capacity to sense, interpret, and respond to subsequent signals. Through this recursive process, adaptation accelerates, and competitive advantage deepens [3, 9, 26]. Unlike linear models of organizational learning that treat knowledge as an output, this process theory conceptualizes learning as a perpetual, endogenous dynamic. The architecture itself becomes the primary strategic asset, where the ability to learn—rather than any particular learned capability—constitutes the enduring source of competitive differentiation.			
Nature of organizational memory	Static archives, documents, routines, and tacit recall	Continuously updated digital memory, models, knowledge graphs, and codified signals	Memory is dynamic and adaptive				
Capability development logic	Incremental improvement through infrequent reflection	Capability renewal through repeated sensing–interpreting–acting–updating cycles	Capabilities are renewed through continuous interaction				
Error correction mechanism	After-action review or managerial intervention	Continuous market response monitoring and automated/assisted adjustment	Adaptation is ongoing and iterative				
Path dependency	Driven by routines and legacy experience	Driven by early-cycle data choices, model design, and feedback interpretation	Initial conditions shape knowledge trajectories				

This architecture gives rise to the following theoretical propositions, which collectively articulate a causal architecture wherein data interaction supplies inputs, market feedback supplies evaluative mechanisms, and iterative cycles supply the engine of knowledge co-evolution.

Proposition 1: Data interaction intensity and knowledge development

Greater data interaction intensity in digital firms positively enhances the speed and depth of organizational knowledge development by expanding the raw material available for analytics-driven insight generation [1, 2, 10, 28]. This proposition posits a direct relationship between the volume, velocity, and variety of data with which an organization actively engages and its ability to develop novel, actionable insights. Intensity here refers not merely to data accumulation but to the frequency and granularity of data interrogation across functional boundaries.

Proposition 2: Market feedback as a mediating mechanism

Market feedback mechanisms serve as a critical mediator, converting data-derived insights into refined dynamic capabilities, thereby enabling continuous strategic adaptation [3, 4, 9, 19]. Insights, without the corrective and evaluative force of market response, remain speculative. This proposition positions feedback as the mechanism that validates, refutes, or refines insights, transforming them into externally validated capabilities. It is through this mediation that learning becomes adaptive rather than merely accretive.

Proposition 3: Analytics capabilities as the central engine

Analytics capabilities serve as the central engine of learning cycles by accelerating the translation of data inputs into interpretable knowledge stocks that accumulate as digital organizational memory [10, 14, 22, 28]. This proposition identifies analytics—encompassing both technological infrastructure and human analytical skill—as the critical throughput mechanism. Without robust analytics, data remains inert, and feedback remains noise. The speed and sophistication of analytical processing directly determine the learning cycle time and the fidelity of the knowledge accumulated.

Proposition 4: Path-dependent knowledge trajectories through iterative feedback

Iterative feedback loops within digital learning systems create path-dependent knowledge trajectories in which early-cycle adaptations amplify the firm's capacity to detect and respond to weak market signals in subsequent cycles [7, 12, 26]. This proposition introduces a temporal and recursive dynamic. Early successes or failures in interpreting feedback shape subsequent data-collection priorities, analytical model development, and interpretive schemas. As a result, firms develop idiosyncratic learning pathways; initial conditions and early cycle outcomes exert a lasting influence on the future trajectory of capability development.

Proposition 5: Hybrid architectures and the closure of feedback loops

Hybrid human–machine learning architectures strengthen the closure of feedback loops by distributing cognitive load and enabling real-time knowledge co-creation across organizational boundaries [14, 20, 22]. Closure—the completion of a full cycle from data to insight to action to feedback and back to memory—is the critical condition for learning to compound. This proposition asserts that hybrid architectures, in which algorithms handle pattern recognition and scale, are effective. At the same time, humans supply contextual judgment, ethical reasoning, and strategic framing, and are uniquely capable of achieving consistent loop closure. Such architectures prevent bottlenecks that would otherwise break the learning cycle, whether due to human cognitive limits or algorithmic rigidity.

Proposition 6: Increasing returns to learning and sustained competitive advantage

Continuous knowledge accumulation through data–feedback cycles generates increasing returns to learning, such that firms with mature digital learning architectures achieve sustained competitive advantage over rivals reliant on episodic learning models [1, 3, 11, 27]. This final proposition articulates the framework's competitive logic. Episodic learning—characterized by periodic strategic reviews, retrospective analyses, and project-based post-mortems—yields linear, intermittent returns. In contrast,

continuous learning architectures exhibit increasing returns: each cycle lowers costs and improves subsequent cycle accuracy, creating a compounding advantage that is difficult for competitors to replicate without undertaking a parallel architectural transformation.

Toward a unified causal architecture

Collectively, these propositions articulate a unified causal architecture that reframes the digital firm as a perpetually learning system. The architecture operates through three interconnected layers:

1. Input layer: Data interaction (Proposition 1) supplies the raw material.
2. Process layer: Analytics capabilities (Proposition 3) and hybrid human–machine architectures (Proposition 5) transform inputs into insights and ensure loop closure.
3. Feedback and adaptation layer: Market feedback mechanisms (Proposition 2) mediate the translation of insights into refined capabilities, while iterative cycles create path-dependent trajectories (Proposition 4) that generate increasing returns (Proposition 6).

This framework advances a dynamic, processual understanding of digital firms, moving beyond static resource-based views to emphasize the recursive mechanisms through which knowledge is continuously co-evolved. By specifying the causal pathways and mediating processes, the theory provides both a conceptual foundation for scholarly inquiry and a practical blueprint for managers seeking to architect their organizations for perpetual adaptation.

Figure 1 presents the conceptual model. It depicts a circular learning loop with five interconnected phases.

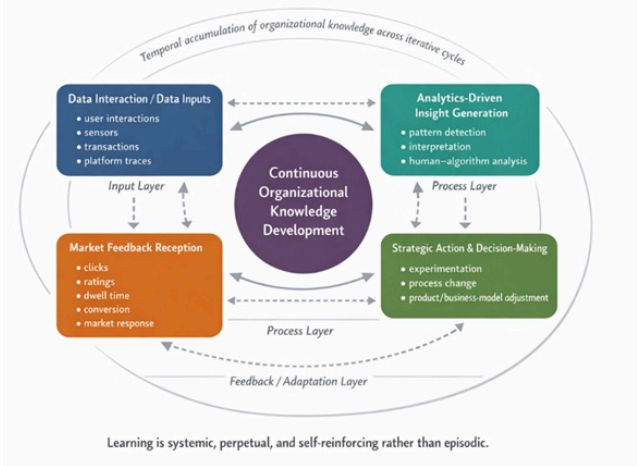


Figure 1. Digital firms as continuous learning systems

Table 2 consolidates the article’s six propositions into a unified causal matrix, clarifying how specific mechanisms, enabling conditions, and observable indicators jointly explain continuous organizational knowledge development.

Table 2. Theoretical consolidation matrix for continuous knowledge development in digital firms

Proposition/core construct	Causal logic advanced in the manuscript	Key mediator or enabling condition	Expected knowledge outcome
P1. Data interaction intensity	Greater intensity of data interaction increases the speed and depth of knowledge development by expanding the analyzable raw material	Cross-functional access to data and frequency of data interrogation	Faster generation and opportunity for recognition
P2. Market feedback as mediator	Market feedback converts internally generated insights into refined capabilities by validating or	Feedback visibility, timeliness, and measurability	More adaptive external capabilities and learning

	disconfirming action outcomes		
P3. Analytics capabilities as an engine	Analytics capabilities translate raw inputs into interpretable knowledge stocks that can accumulate as organizational memory	Quality of analytics infrastructure plus analytical human expertise	Hi learn fidel stre me for
P4. Iterative feedback and path dependency	Repeated cycles produce path-dependent knowledge trajectories because early interpretations shape later data priorities and schemas	Persistence of model choices and learning routines over time	Cum hist conc lea traje
P5. Hybrid human–machine architecture	Human–machine complementarity strengthens loop closure by combining scale-based pattern recognition with contextual judgment	Role clarity between algorithms and human decision-makers	M con robu scale cre lea
P6. Increasing returns to learning	Repeated successful cycles lower the cost and improve the accuracy of subsequent learning cycles, generating a sustained advantage	Architectural maturity and consistency of loop closure	Comp lea bene du adv

System-level boundary conditions	The strength of all six mechanisms depends on whether the firm can sustain loop integrity under contextual constraints	Regulatory burden, privacy limits, data quality, technological maturity, resource slack	Ampl or atte of cor lea ef
System breakdown risks	Learning weakens when one or more phases fail to connect tightly to the next phase	Broken feedback loops, siloed data, low trust in analytics, and weak memory updating	Frag know accur and r adap

From Theory to Practice in Feedback-Driven Digital Ecosystems

Orchestrating feedback-driven capability renewal

The conceptual architecture developed above transcends a purely descriptive function; it offers a prescriptive blueprint for digital firms seeking to embed continuous learning as their core operating logic. Moving beyond static strategic planning, managers can operationalize the proposed five-phase learning loop by fundamentally restructuring their organizations around data flows rather than traditional functional silos [3, 9, 20]. This shift necessitates a move from linear value chains to dynamic, interconnected networks. For instance, leading platform firms—such as those examined in dynamic-capability research—deliberately embed real-time analytics dashboards that trigger automated sensing routines. This infrastructure empowers cross-functional teams to act on market feedback within minutes, compressing cycles that once took quarters [1, 2, 14].

This orchestration of capability renewal requires deliberate investment in sophisticated hybrid human–machine

interfaces. Within these interfaces, learning responsibilities are distributed according to comparative advantage: algorithms excel at pattern detection at scale, processing vast datasets to identify emerging trends and anomalies, while human experts provide indispensable contextual judgment, strategic interpretation, and ethical oversight [14, 22]. This symbiotic relationship ensures that machine efficiency is tempered with human wisdom, preventing the automation of flawed processes and enabling nuanced responses to complex market signals.

Evidence from analytics-capability research substantiates this approach, demonstrating that firms with higher data interaction intensity also report significantly faster capability renewal. This acceleration is particularly pronounced when feedback loops are closed through integrated customer-experience platforms that unify data from marketing, sales, and service functions [10, 28]. In practical terms, this means migrating from static knowledge repositories—such as traditional intranets or document libraries—to living digital memory systems. These are embodied in cloud-based knowledge graphs that automatically update with each cycle of insight, action, and feedback, ensuring that organizational knowledge is not a record of the past but a dynamic resource for the present [11, 17].

Such systems create compounding returns, establishing a virtuous cycle of improvement. Early-cycle adaptations refine data-collection algorithms, leading to more precise targeting and data quality. This, in turn, sharpens subsequent market-signal detection and reduces noise in the learning process, enabling organizations to distinguish between fleeting fads and substantive shifts with greater accuracy [4, 26].

The efficacy of this internal architecture is further amplified through boundary-spanning practices. Digital firms increasingly form ecosystem partnerships that extend their learning loops beyond firm borders, incorporating critical data streams from suppliers, competitors, and even regulators [5, 7, 12]. This outward orientation cultivates a meta-learning capability—the capacity to learn how to learn across ecosystems. This represents an advanced stage of the model where organizational memory becomes distributed yet synchronized through shared APIs and common analytics protocols, creating a unified intelligence that spans the value network [13, 27]. Managers who approach capability renewal not as a cultural initiative but as an engineering challenge—focused on system architecture, data integrity, and interface design—are better

positioned to sustain a competitive advantage, as the architecture itself becomes a proprietary source of increasing returns to learning [1, 3, 11].

Emerging horizons in digital organizational learning theory

While the proposed framework successfully integrates and extends existing streams of research, several boundary conditions and avenues for future inquiry warrant explicit recognition to ensure its continued evolution and applicability.

Contextual contingencies and resource constraints

The intensity of data interaction and the velocity of feedback loops are not uniform across all digital firms. Resource-constrained startups may lack the critical mass of data or analytical talent to complete full cycles, while legacy organizations undergoing partial digitalization may experience truncated cycles that limit knowledge accumulation, leading to fragmented insights [6, 8, 19]. Contextual moderators—such as industry-specific regulatory regimes, data-privacy constraints, and the organization's technological maturity—therefore shape the strength of the theoretical propositions [4, 5, 28, 29]. Future empirical work should test these contingencies through longitudinal case studies or configurational analyses (e.g., Qualitative Comparative Analysis) to map how different learning-system architectures lead to varying performance outcomes across diverse contexts.

Governance, power, and the locus of learning

The framework raises critical questions about the locus and ownership of learning in increasingly decentralized platform ecosystems. As machine learning algorithms substitute for portions of human decision-making, power asymmetries between platform owners and participants become more consequential [14, 22]. Scholars must examine how these asymmetries affect knowledge co-creation and memory formation. For instance, Propositions 3 and 5, which relate to feedback loop velocity and ecosystem learning, could be refined by investigating governance mechanisms. Research is needed to identify structures—such as data trusts, algorithmic auditing boards, or transparent contribution metrics—that ensure an equitable distribution of learning benefits while proactively mitigating algorithmic bias and preventing exploitative data practices [10, 20].

The temporal dynamics of knowledge accumulation

The temporal dimension of knowledge accumulation invites dynamic modeling that goes beyond linear progression. Although the conceptual spiral illustrates increasing returns, the field has yet to quantify the rate at which digital organizational memory compounds. Future research should explore the inflection points at which increasing returns may plateau or at which diminishing returns and path dependency may emerge, potentially locking organizations into suboptimal learning trajectories [12, 26]. Simulation studies and process-tracing methods offer promising methodological approaches for examining these trajectories across multiple cycles, providing insights into the optimal cadence and sequencing of learning activities.

Interdisciplinary cross-pollination

Finally, the richness of the learning-system perspective can be substantially enhanced through cross-pollination with adjacent fields. Integrating insights from behavioral strategy can illuminate micro-level mechanisms, such as individual sensemaking and cognitive biases within algorithmic environments. Collaboration with information systems ethics can provide robust frameworks for addressing the normative challenges of automated decision-making. Similarly, leveraging methods from computational social science can help model macro-level outcomes, such as the emergence of industry-wide learning ecosystems and their impact on market dynamics [11, 23, 24]. These interdisciplinary horizons ensure that the learning-system perspective remains generative rather than exhaustive, inviting scholars to test, extend, and contextually ground its six propositions across diverse empirical settings.

Reimagining Digital Firms as Perpetual Learning Systems

Digital firms are no longer best understood through static resource or capability lenses; they are living systems whose competitive advantage derives from the perpetual co-evolution of data, knowledge, and market feedback. By synthesizing three previously siloed literatures—big data

analytics, dynamic capabilities, and digital transformation—into a unified process theory, this article has demonstrated how continuous learning loops transform raw interaction data into refined organizational memory and adaptive strategic action. The six propositions articulate precise mechanisms through which feedback-driven architectures generate increasing returns to learning, while **Figure 1** supplies a visual scaffold for both theoretical refinement and managerial application.

Ultimately, the framework shifts the theoretical conversation from episodic adaptation to perpetual renewal. In an era of accelerating digitalization, firms that embed learning cycles at the core of their architecture will outpace rivals whose knowledge development remains tethered to traditional, slower rhythms. The theory thus offers both scholars and executives a forward-looking lens: one that foregrounds data interaction and market feedback not as supporting technologies but as the very heartbeat of organizational intelligence. As digital environments continue to evolve, so too must our understanding of how firms learn—continuously, collectively, and in symbiosis with the markets they serve.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 05 Apr 2023 Revised: 15 May 2023 Accepted: 10 Jul 2023

Published online: 18 September 2023

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