

The New Competitive Edge: The Learning Power of Firms

Y. Doz and S. Dutta

*Solvay Chaired Professor of Technology Innovation Emeritus, INSEAD, France
Former Founding Dean, SC Johnson College of Business, Cornell University, USA*

At Amazon, millions of pricing and recommendation decisions update continuously as customers browse, click, and buy. At Netflix, every interaction refines what gets recommended next. At Stripe, each transaction sharpens fraud detection and reliability across the network.

What is striking is not just the sophistication of these systems, but the way they learn. None of this learning waits for a meeting. It happens as the organization operates. Every interaction generates data. Every decision produces feedback. Every outcome becomes an input for the next action.

For decades, managers understood learning as something that followed action. Organizations acted first and learned later, through reflection, analysis, and discussion. That sequence is changing. Today, learning is increasingly embedded within action itself. Systems do not simply execute decisions; they update them continuously. Organizations are learning as they act.

This is not just faster learning. It is a different kind of capability. Competitive advantage is shifting to the learning power of the firm: the ability to generate, propagate, and apply learning at scale. The winners will not be those with the best plans or even the best capabilities. They will be those whose systems learn and adapt at machine speed.

A New Competitive Lens: The Learning Power of Firms

In organizations shaped by AI, learning is no longer a background capability. It becomes a primary driver of performance. It can be understood through four dimensions.

The first is **learning density**: how much insight an organization extracts from each interaction. Every customer click, transaction, service call, or operational event can both pass through the system as a completed task and become a source of learning that improves future behavior. A customer transaction may inform recommendations, pricing, demand forecasting, inventory positioning, logistics planning, and customer segmentation. High learning-density organizations are designed so that nothing is wasted. Every action teaches.

Amazon illustrates this logic. A single customer interaction can feed multiple systems at once: recommendation models, pricing algorithms, fulfillment decisions, and inventory planning. Meta Platforms shows a similar pattern. Every user interaction can inform ranking algorithms, advertising models, safety systems, and engagement tools.

By contrast, many organizations generate large volumes of activity but little learning. A sale is completed, but the underlying signals are not fully captured. A decision is made, but feedback is not systematically integrated. Data exists, but it is fragmented across systems. Low density does not mean a lack of data. It means a failure to convert activity into insight.

The second dimension is **learning velocity**: how quickly an organization translates insight into changed behavior. In high-velocity organizations, the gap between learning and action is compressed, often to near zero. Insights do not sit in reports or wait for approval cycles. They are incorporated into how the system (comprising both humans and agentic AI) operates.

At Netflix, user behavior feeds directly into recommendation systems, which adjust continuously. At Stripe, fraud signals detected in one part of the network rapidly inform decisions elsewhere. At Amazon, pricing, inventory, and fulfillment decisions are updated as new data arrives.

The problem in many traditional organizations is not a lack of insight. It is the delay between knowing and doing. High learning velocity requires real-time data flows, automated decision pipelines, and embedded execution logic.

The third dimension is **learning scale**: the number of learning processes an organization can run simultaneously. In traditional organizations, learning is constrained by human capacity. AI changes that constraint. Thousands, even millions, of learning processes can operate at once.

At Booking.com, experimentation is pervasive, continuously refining search results, pricing displays, and user interfaces. At Alphabet, models evolve across products, markets, and use cases, drawing on massive streams of data and feedback.

Scale does not just increase the volume of learning. It changes its nature. Organizations can discover patterns, test strategies, and refine decisions at a breadth and speed that was previously impossible. But scale alone is not enough. Without density, it produces noise. Without velocity, it produces delayed impact. Combined with density and velocity, learning scale becomes a powerful multiplier.

The fourth dimension is **learning directionality**: the alignment of learning objectives with strategic intent and organizational values. A learning system optimizes relentlessly against whatever objective it has been given. When that objective is well-specified and aligned with what the organization genuinely values, fast learning is a powerful competitive advantage. When the objective is incomplete or misaligned, fast learning accelerates in the wrong direction. Dynamic pricing can erode customer trust if optimized narrowly for short-term revenue. Recommendation systems can amplify polarizing content when engagement is the only metric. Supply chains can optimize cost at the expense of resilience. Financial models can chase short-term returns while underestimating risk. In each case the system functions exactly as designed. The problem is not a failure of learning. It is a failure of direction. Directionality is what ensures that speed, scale, and density compound toward outcomes the organization actually intends.

Together, these four dimensions define the learning power of the firm:

An organization with high density but low velocity learns too slowly. One with high velocity but low scale improves only in narrow domains. One with scale but low density generates vast amounts of data but little insight. The firms pulling ahead combine all four: extracting insight from every interaction, translating it into action quickly, and doing so at scale across thousands of parallel processes.

From Learning Units to Learning Surfaces

Traditionally, learning was concentrated in specific parts of the organization: strategy teams, R&D units, post-mortems, leadership reviews, and planning processes. Learning was episodic, structured, and relatively scarce.

In AI-enabled organizations, learning is distributed across the entire system. Every interaction becomes a source of feedback. Every operational edge becomes a point of adaptation.

At Uber, each ride updates pricing, matching, and routing algorithms. At Tesla, driving data feeds autonomous-driving models. At Booking.com, experiments run continuously across the customer interface.

Learning is no longer confined to a department or process. The organization becomes a **learning surface**: a distributed system in which interactions at the edge generate feedback and contribute to improvement. This shift from centralized learning to distributed learning surfaces makes high density, velocity, and scale possible.

These ideas build on a rich tradition of organizational learning, but they also extend it. Chris Argyris and Donald Schön focused on how firms detect and correct errors, distinguishing between incremental adjustment and deeper shifts in assumptions. James March highlighted the tension between exploration and exploitation. David Teece emphasized dynamic capabilities: the ability to sense change and reconfigure resources over time.

These perspectives remain essential. But they were rooted in a world where learning was largely human-centered, episodic, and mediated through organizational processes. In AI-enabled organizations, learning is increasingly embedded in agentic AI, not just in people. It is continuous, not periodic. It is distributed, not concentrated. And it can be executed in real time, not only after reflection.

The challenge is no longer simply to become a “learning organization.” It is to design a learning surface where learning is ubiquitous, immediate, scalable across the organization, and aligned with strategic intent.

New Logics of Learning: Beyond Human Learning

The transformation underway is not simply that organizations are learning faster. They are beginning to learn in ways that were previously impossible.

For most of modern management history, learning was constrained by human cognition: what individuals could observe, interpret, and imagine. AI systems, and increasingly agentic AI systems, are breaking those constraints.

Reinforcement learning systems improve by interacting with an environment, testing actions, and optimizing against feedback. At Alphabet, such systems have optimized data-center cooling by discovering strategies beyond human intuition. Agentic systems extend this further. They can pursue goals over time, sequence decisions, and adapt dynamically, learning not just within single choices but across chains of action.

A second shift is continuous re-optimization. At Amazon, pricing is recalculated as signals change. Learning becomes ongoing re-computation and continuous optimization.

A third shift is large-scale pattern discovery. At Meta, models detect behavioral patterns across billions of interactions — signals no human could identify. Agentic systems can link this discovery directly to action, testing and refining continuously.

Learning is shifting from reflection to optimization and exploration; from incremental adjustment to continuous reconfiguration; and from human interpretation to system-driven discovery at scale. AI does not just accelerate learning. It expands what can be learned. But that expansion makes the fourth dimension of learning power — directionality — more critical, not less. The question is not only how much and how fast the organization learns, but toward what end.

From Learning to Governed Learning: The Strategic Envelope

If learning at machine speed is the new source of advantage, governance becomes the source of stability. This is where strategy re-enters the picture. Left unconstrained, learning systems will optimize relentlessly, but not necessarily in ways that align with broader goals. The challenge is not to slow learning, but to shape it: to ensure that it unfolds within boundaries that preserve coherence, trust, and long-term value.

At Capital One, machine learning models must meet thresholds for fairness, stability, and explainability before influencing decisions. At Amazon, system architecture contains failures, limits cascading effects, and prevents local optimizations from destabilizing the broader system. At Netflix, new features are introduced incrementally and monitored closely, with rollback mechanisms when performance falls outside acceptable ranges.

In each case, the organization is not reducing its capacity to learn. It is governing how learning occurs. This is the essence of the **strategic envelope**. Learning systems are allowed to explore, adapt, and improve, but within boundaries that specify what is acceptable, what is not, and when human intervention is required.

The firms that succeed will not be those that simply learn the fastest, but those that combine speed with control.

The New Role of Leadership

As learning becomes embedded in systems, leadership changes fundamentally. In the past, leaders were primarily decision-makers: setting direction, allocating resources, and ensuring execution. Today, many decisions are made continuously by systems. Learning happens across the organization, often without direct human intervention.

Leadership therefore shifts from directing actions to designing and governing the systems that learn and act. The central task is not to make every important decision. It is to ensure that learning processes operate at sufficient density, velocity, and scale — while remaining aligned with strategic intent.

Leaders must ask: Where is learning actually happening? What signals are being captured, and which are being missed? How quickly does learning translate into changed behavior? Where might learning drift in ways that undermine strategy or values?

These are not technical questions to be delegated. They are strategic questions about how the organization performs and evolves. In the age of AI, strategy is not only what leaders decide. It is how their systems are designed to learn.

What Remains Human

As organizations become increasingly driven by AI, it is tempting to see learning itself as becoming fully automated. Systems can optimize decisions, adapt in real time, and detect patterns at a scale and complexity beyond human capability.

But systems do not define purpose. They do not establish legitimacy. A recommendation system can learn what keeps users engaged. It cannot determine whether that engagement is desirable. A pricing system can optimize revenue. It cannot decide what constitutes fairness. A risk model can detect anomalies. It cannot judge what level of risk is appropriate.

Systems can learn faster. But they cannot decide what is worth learning. That responsibility remains human. Leaders must define the objectives that systems pursue, the constraints within which they operate, and the values they must uphold. They must interpret ambiguous signals, weigh competing priorities, and ensure that the organization's actions remain legitimate in the eyes of customers, regulators, and society. AI does not replace human judgment. It makes it indispensable.

Conclusion: The New Frontier of Competition

For much of modern business history, competitive advantage followed a familiar trajectory. Organizations first competed on resources: access to capital, talent, and assets. Over time, the focus shifted to capabilities. More recently, advantage has been tied to learning: the ability to adapt, improve, and respond to change.

That progression is now moving further. Competition is increasingly defined by the architecture and physics of learning systems. What distinguishes leading firms is not simply what they know, or even how quickly they adapt in discrete moments. It is their **learning power**: the ability to learn continuously, at scale, and in alignment with strategic intent.

Organizations like Amazon, Netflix, and Stripe are not just executing strategy. They are operating systems that sense continuously, learn everywhere, improve rapidly, and remain aligned within defined boundaries. Their advantage comes from turning the organization into a **learning surface** — a distributed system in which every interaction, transaction, and operational edge can generate feedback — while governing that learning within a **strategic envelope** that defines what is acceptable, what is not, and when human judgment must intervene.

In these organizations, strategy is not a plan that is periodically implemented. It is a set of conditions that shape how the system learns and evolves over time. The firms that lead will not be those with the best initial strategy. They will be those whose systems have the greatest learning power — and whose leaders know how to direct, bound, and govern that power.

Organizations are no longer defined primarily by what they know. They are defined by how their systems generate, propagate, and govern learning. In the age of AI, that learning is no longer occasional or localized. It happens across the learning surface, inside a strategic envelope, everywhere, all the time, at machine speed.

The new competitive edge is not simply learning. It is **learning power** — and the ability to shape it.

Disclosure: AI was used for research and copy editing in the writing of this paper.