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Digital Strategy as Continuous Experimentation: Rethinking Organizational Planning in Data-Rich Business Environments

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Abstract

In data-rich business environments, traditional strategic planning—built on long-term forecasts, annual budgets, and fixed resource allocation—has become increasingly ineffective. Digital markets reward speed, iteration, and real-time adaptation rather than prediction and control. This managerial perspective article argues that digital strategy must be reconceptualized as continuous experimentation: a strategic logic in which hypothesis generation, rapid testing, data-driven learning, and iterative decision-making replace static plans. Drawing on recent scholarship in digital transformation, agile strategy, and organizational learning, the article demonstrates how leading firms operationalize experimentation through A/B testing platforms, real-time analytics, and cross-functional feedback loops. A new strategic framework—the Continuous Experimentation Strategy Loop—is introduced to guide managers in embedding experimentation into core planning processes. The framework highlights six interlocking elements: hypothesis generation, rapid experimentation, data capture and analytics, learning and insight generation, decision and iteration, and scaling with feedback loops. Practical implementation challenges, including organizational structures, cultural barriers, and risks of over-testing, are examined. The article concludes that in volatile, data-abundant contexts, the ability to experiment continuously is not a tactical tool but the central mechanism of strategic renewal. Managers who treat strategy as perpetual experimentation gain superior adaptability, faster innovation cycles, and sustained competitive advantage.

Keywords Organizational learning, Data-driven decision-making, Digital strategy, Continuous experimentation, Agile planning, Iterative strategy

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Introduction

Digital technologies have fundamentally altered the pace, predictability, and information intensity of competition. Where once managers could rely on multi-year strategic plans and stable industry structures, today's data-rich environments are characterized by rapid technological change, platform dynamics, and continuous customer feedback loops. Amazon, Netflix, and Alibaba, for example, no longer treat strategy as a fixed roadmap; instead, they

operate through thousands of simultaneous experiments that shape product features, pricing, and even business models in real time. This shift signals a deeper transformation: digital strategy is moving from static planning to continuous experimentation [1-4].

Traditional strategic management literature, rooted in industrial-era assumptions, emphasized foresight, resource allocation, and sustainable competitive advantage through positioning. Yet these assumptions erode in environments

where customer preferences evolve daily, competitors emerge overnight, and data volumes grow exponentially. Long-term planning cycles—often spanning 12–36 months—create rigidity that digital-native firms exploit through rapid iteration. Research on digital transformation consistently shows that pre-digital organizations struggle precisely because their planning processes remain anchored in linear, prediction-based logic [5-8].

The core thesis of this article is that experimentation must become the dominant strategic logic for organizations operating in data-rich settings. Experimentation here is not merely tactical (e.g., website optimization) but strategic: a deliberate, organization-wide process that replaces annual planning rituals with adaptive cycles of hypothesis testing, learning, and adjustment. This perspective aligns with emerging scholarship on agile strategy, real-time organizational learning, and platform-based innovation [9-18]. Continuous experimentation enables firms to reduce uncertainty, accelerate innovation, and reconfigure resources dynamically without sacrificing strategic coherence.

This managerial perspective article proceeds in three parts. First, it analyzes the strategic challenge posed by traditional planning in digital markets, highlighting failures of control-oriented approaches and the necessity of flexibility. Second, it presents a practical framework—the continuous experimentation strategy loop—that operationalizes strategy as iterative experimentation. The framework integrates six core components supported by real-world managerial practices and recent empirical insights. Throughout, the discussion maintains a managerial focus, emphasizing actionable implications for executives rather than statistical validation. By reframing digital strategy as continuous experimentation, the article equips leaders with a new mental model for navigating data-rich environments where the only constant is change [1, 2, 12]. **Table 1** contrasts traditional planning-based strategy with continuous experimentation logic, highlighting a fundamental shift from prediction and control toward learning-driven adaptation as the primary source of competitive advantage.

Table 1. Structural comparison of strategic logics: planning vs continuous experimentation

Dimension	Traditional strategic	Continuous experimentation,
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	planning logic	strategic logic
Temporal orientation	Long-term, periodic (annual/multi-year cycles)	Continuous, real-time, and iterative cycles
Core assumption	Predictability and environmental stability	Uncertainty and constant environmental change
Strategic mechanism	Forecasting, planning, and resource allocation	Hypothesis testing, experimentation, and learning
Decision-making mode	Top-down and centralized	Distributed, cross-functional, and data-informed
Role of data	Retrospective analysis and reporting	Real-time feedback and causal inference
Resource allocation	Fixed budgets tied to predefined plans	Dynamic allocation across experimentation portfolios
Error management	High cost and difficult to reverse	Low-cost, reversible, and iterative correction
Organizational learning	Episodic and post-hoc learning	Continuous and embedded learning loops
Speed of adaptation	Slow, constrained by planning cycles	Rapid, driven by experimentation velocity
Governance logic	Control, compliance, and predictability	Flexibility, guardrails, and adaptive governance
Performance metrics	Plan adherence, ROI, and forecast accuracy	Learning velocity, experiment throughput, and insight adoption
Risk profile	Risk is concentrated in	Risk is distributed across multiple small

	large strategic bets	experiments
Competitive advantage source	Positioning and resource ownership	Learning speed and adaptive capability

Strategic Challenge of Continuous Experimentation

Traditional strategic planning assumes a degree of environmental stability that no longer exists in digital markets. Five-year forecasts, detailed implementation roadmaps, and centralized resource commitments create organizational inertia precisely when agility is required [19–25]. In data-rich contexts, customer behavior, competitor moves, and technological possibilities shift faster than planning cycles can accommodate. A notable example is the retail sector, where legacy firms with rigid annual merchandising plans have been outmaneuvered by platforms that adjust assortments, pricing, and recommendations in hours based on live experimentation [8, 16].

The failure of traditional planning stems from three interrelated dynamics. First, uncertainty has intensified. Digital technologies compress product life cycles and lower entry barriers, making long-term prediction unreliable [20]. Second, data abundance paradoxically complicates decision-making: without systematic experimentation, organizations drown in signals yet lack causal insight [13]. Third, the cost of strategic error has risen. A misaligned multi-year plan can consume millions before correction, whereas experimental approaches allow small, reversible bets [6, 15].

Scholars have documented this tension across multiple streams. Research on agile strategy demonstrates that iterative planning outperforms linear approaches in volatile settings [9, 22]. Studies of digital transformation reveal that firms succeeding in strategy renewal treat planning as a learning process rather than a control mechanism [7, 8]. Platform literature further shows that experimentation is not optional but constitutive: platforms derive value from continuous product iteration and ecosystem feedback [11, 19].

Yet shifting to continuous experimentation entails non-trivial trade-offs. Control versus flexibility remains central.

Traditional planning offers coordination and accountability; experimentation introduces ambiguity and requires tolerance for failure [5, 6]. Resource allocation also changes: budgets must shift from fixed projects to dynamic experimentation portfolios [14]. Cultural resistance is common—managers accustomed to “getting it right the first time” must embrace “fail fast, learn faster” [2, 18]. Over-experimentation risks decision fatigue, statistical noise, and customer annoyance if poorly managed [13].

Organizational learning theory provides a useful lens. Experimentation converts tacit market signals into explicit, actionable knowledge [9, 10]. However, learning only accrues when experiments are designed with clear hypotheses, proper controls, and rapid feedback mechanisms [1, 3]. Without these, firms risk generating data without insight—a common pitfall in large-scale A/B testing programs [13, 26–29].

The strategic imperative is therefore clear: in data-rich environments, competitive advantage accrues to organizations that institutionalize experimentation as the primary mode of strategy-making. This requires rethinking governance, metrics, and leadership behaviors. The following section translates this imperative into a practical managerial framework.

Designing Strategy as an Iterative Experimentation System

To move from aspiration to execution, digital strategy must be designed as an integrated experimentation system. The proposed continuous experimentation strategy loop (Figure 1) offers a managerial framework comprising six interconnected components that replace linear planning with adaptive cycles.

The loop begins with hypothesis generation, where cross-functional teams translate strategic objectives into testable assumptions about customer behavior, product features, or operational processes [5, 15]. Next comes rapid experimentation, typically executed through A/B testing, multivariate experiments, or controlled pilots on digital platforms [3, 11]. Data capture and analytics follow, leveraging real-time dashboards and advanced analytics to ensure causal inference rather than correlation [12, 13]. Learning and insight generation convert raw results into organizational knowledge, often through structured debriefs

and knowledge repositories [9, 18]. Decision and iteration then occur: successful variants are scaled, unsuccessful ones are terminated, and new hypotheses are formulated [1, 2]. Finally, scaling successful experiments integrates learnings into core operations while maintaining feedback loops that inform hypothesis generation [6, 14].

This cyclical design ensures the strategy remains dynamic. Real-time adjustment mechanisms—enabled by cloud infrastructure and automated experimentation platforms—allow decisions at the speed of data rather than the speed of quarterly reviews [12, 16].

Figure 1 illustrates the framework visually as a continuous loop with embedded feedback arrows, emphasizing that learning never stops and scaling itself generates new hypotheses.

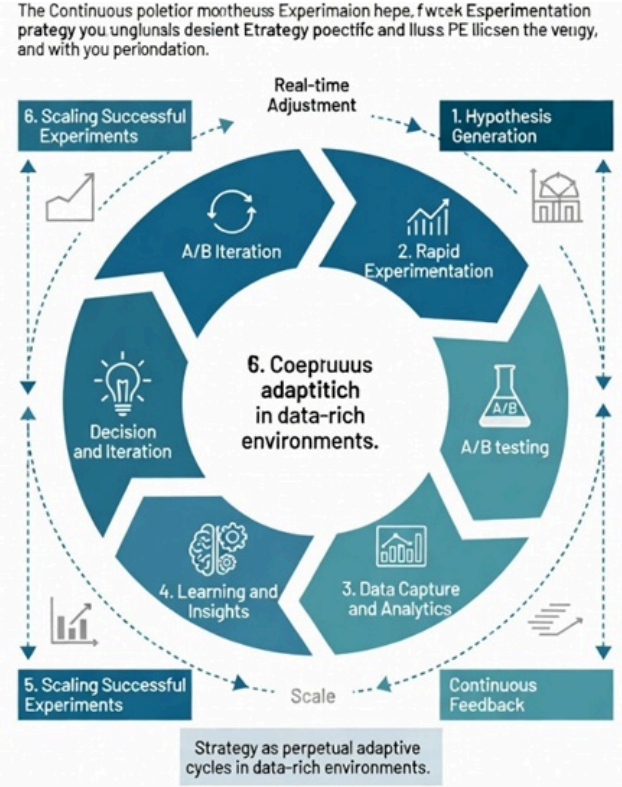


Figure 1. Continuous experimentation strategy loop. The figure depicts strategy as a perpetual cycle of hypothesis generation, rapid experimentation, data capture and analytics, learning, decision and iteration, and scaling—with continuous real-time feedback loops enabling adaptive strategic renewal.

Operationalizing the framework demands specific organizational structures. Dedicated experimentation

teams, centralized analytics platforms, and senior sponsorship are essential [2, 3]. Risk management is equally critical: firms must guard against over-testing (customer fatigue), noisy data (false positives), and misinterpretation (selection bias) [13, 29]. Governance mechanisms, such as experimental review boards and ethical guidelines, help balance innovation with responsibility [19].

When implemented holistically, the Continuous Experimentation Strategy Loop transforms digital strategy from a periodic exercise into an ongoing organizational capability. Managers who master this system gain the ability to sense weak signals, test bold ideas at low cost, and reallocate resources dynamically—precisely the competencies required in data-rich business environments [8, 12, 20].

Table 2 systematizes the governance architecture required for continuous experimentation, demonstrating how disciplined oversight mechanisms transform experimentation from a source of risk into a driver of reliable strategic learning.

Table 2. Governance and risk architecture in continuous experimentation systems

Risk domain	Key challenge	Underlying mechanism	Strategic consequence
Over-experimentation	Excessive simultaneous tests	Lack of prioritization and coordination	Decision fatigue and diluted focus on high-potential experiments
Statistical noise and false positives	Misleading results from weak designs	Poor hypothesis specification and small samples	Increased strategic uncertainty and wasted resources
Data fragmentation	Isolated insights across teams	Lack of centralized data infrastructure	Low organizational learning and delayed strategic adaptation

Interpretive bias	Misreading experimental outcomes	Cognitive bias, overreliance on short-term metrics	Suboptimal decision-making
Customer fatigue	Excessive variation in user experience	High-frequency testing in customer-facing systems	Reduced satisfaction and brand loyalty
Ethical and privacy risks	Unintended harm or unfair treatment	Intensive data collection and algorithmic targeting	Reputational damage and regulatory exposure
Strategic drift	Misalignment with long-term goals	Local optimization without strategic coherence	Fragile strategic execution
Capability gaps	Lack of experimentation skills	Managers trained in planning, not testing	Superficial experimentation

Operationalizing Continuous Experimentation: Managerial Levers for Execution

The Continuous Experimentation Strategy Loop provides the conceptual architecture, yet its value materializes only when leaders deliberately redesign structures, technology stacks, and cultural norms to support perpetual testing [2, 3, 18]. Successful digital firms treat experimentation not as a project but as an embedded organizational routine that spans functions and hierarchies.

Redesigning organizational architecture for speed and autonomy

Effective experimentation requires decentralized decision-making rights alongside a centralized learning

infrastructure. Cross-functional “experiment squads” — typically comprising product managers, data scientists, designers, and engineers — operate with rapid sprint cycles rather than annual planning gates [9, 22]. Senior leadership must sponsor experimentation portfolios, allocating ring-fenced budgets (often 10%–20% of total innovation spend) that can be reallocated weekly rather than quarterly [14, 15]. Governance boards review only high-impact experiments, freeing frontline teams to run hundreds of low-stakes tests. This structure mirrors the agile local-government models documented by Drechsler and Soe, where experimentation precedes large-scale commitment [4, 23]. The outcome is faster signal detection and reduced bureaucratic drag in data-rich environments.

Technology enablers: From data silos to real-time experimentation platforms

Robust experimentation requires integrated tooling that connects hypothesis tracking, test deployment, analytics, and knowledge repositories. Modern platforms (e.g., feature-flag systems, automated A/B testing engines, and causal-inference dashboards) enable simultaneous experiments at scale while maintaining statistical validity [11, 13, 29]. Cloud-native architectures further support real-time data capture, allowing decisions within hours rather than weeks [12]. Managers must invest in unified data lakes and experiment registries to prevent duplication and ensure organizational memory. Research on enterprise-system implementation underscores that phased yet agile rollouts of such platforms deliver superior performance gains compared with rigid waterfall approaches [12]. Without these enablers, firms risk generating isolated insights that never inform strategic iteration.

Cultivating a learning culture: Leadership behaviors and incentive realignment

Cultural transformation is often the most demanding and consequential lever in building an experimentation-driven organization. Processes, tools, and analytics infrastructure can be introduced relatively quickly, but reshaping managerial assumptions, performance expectations, and everyday behaviors requires sustained leadership commitment. In firms accustomed to predictive planning and execution discipline, experimentation can be perceived as risky, inefficient, or even threatening because it exposes uncertainty and legitimizes the possibility of failure. For this

reason, senior leaders must actively model the norms they want others to adopt. One of the most important of these norms is intellectual humility: leaders should openly acknowledge when assumptions are wrong, publicly celebrate well-designed failures that generate valuable insights, and share experiment post-mortems that demonstrate how learning improves future decisions [5, 6, 18]. These visible acts reduce the stigma of failure and signal that the organization values disciplined inquiry over defensive certainty.

A learning culture also requires a redefinition of what counts as high performance. In traditional strategy systems, managers are rewarded for delivering against predetermined plans, minimizing deviation, and projecting confidence. In an experimentation-oriented environment, however, these incentives can suppress curiosity and discourage adaptation. Performance metrics, therefore, need to shift from simple adherence to plan toward indicators of learning velocity and decision quality. Relevant measures include experiment throughput, insight adoption rate, time from hypothesis generation to decision, and the number of meaningful strategic pivots or validated refinements achieved per quarter [1, 2]. Such metrics do not reward experimentation for its own sake; rather, they reward the organization's capacity to turn uncertainty into cumulative knowledge. This reorientation helps managers understand that strategic effectiveness lies not in proving initial assumptions correct, but in improving the organization's ability to learn faster than rivals.

Capability development must accompany this shift in incentives. Many mid-level managers have been trained to execute plans, allocate budgets, and monitor key performance indicators, but not necessarily to formulate hypotheses, evaluate causal claims, or interpret statistical evidence. Yet these skills are essential if experimentation is to become embedded in routine strategic work rather than confined to specialist teams. Training programs on hypothesis formulation, experimental design, causal reasoning, and statistical literacy should therefore become mandatory for mid-level managers, who often serve as the bridge between top-level strategy and frontline implementation. Equipping this layer of leadership is particularly important because they translate abstract cultural aspirations into actual operating norms: what gets proposed, what gets funded, how results are interpreted, and which lessons are scaled across the organization. Without such capability building, experimentation risks becoming superficial, with managers either over-trusting

weak evidence or resisting valid findings that challenge established beliefs.

Reward systems must likewise be redesigned to support the new culture. Organizations that previously penalized deviation, punished unsuccessful initiatives, or equated consistency with competence often create strong disincentives for experimentation. Employees quickly learn to avoid proposing bold tests, to frame all outcomes as successes, or to hide ambiguous results. To counter this, evaluation and promotion systems should explicitly recognize "smart failure," rapid iteration, and evidence-based adaptation. Smart failure refers not to careless mistakes, but to disciplined tests of consequential assumptions that produce useful learning even when outcomes are negative. By recognizing teams that stop weak initiatives early, refine ideas in response to evidence, or surface uncomfortable truths before competitors do, leaders reinforce the message that learning is a strategic contribution. Over time, this realignment reduces political behavior around decision-making and makes honest reporting more likely.

Evidence from agile transformations supports the view that cultural alignment, rather than process change alone, determines long-term success [9, 22]. Many firms adopt agile rituals, digital dashboards, or innovation labs without changing the deeper assumptions that govern power, accountability, and legitimacy. In such settings, experimentation remains performative rather than transformative. By contrast, when leaders consistently reward curiosity, transparency, and disciplined adaptation, experimentation becomes a core leadership competency rather than a peripheral method. At that point, organizations begin to develop a form of collective intuition: an institutionally embedded ability to sense weak signals, interpret emerging patterns, and respond to market shifts before they become visible in traditional planning documents [9, 22]. This does not eliminate uncertainty, but it does make the organization more fluent in navigating it.

Navigating Risks and Trade-offs in Experimentation-Driven Strategy

Continuous experimentation introduces new vulnerabilities that must be actively managed rather than ignored. While experimentation can accelerate learning and increase strategic responsiveness, it also creates risks of overload,

misinterpretation, ethical failure, and fragmented decision-making if not properly governed. An experimentation-driven strategy system, therefore, requires not only speed and openness but also discipline, prioritization, and safeguards that preserve the quality and legitimacy of strategic action.

Mitigating over-testing, noise, and decision fatigue

One major risk is the uncontrolled proliferation of tests. When experimentation becomes widely encouraged, teams may launch too many initiatives simultaneously, exposing customers to constant variation, straining analytical resources, and generating statistically noisy results that mislead rather than inform decision-makers [13, 29]. Excessive testing can also create organizational decision fatigue, as leaders are confronted with a continuous stream of partial findings, conflicting signals, and requests for action. In customer-facing settings, over-testing may degrade user experience, weaken brand consistency, or create confusion among important segments. The problem is not experimentation itself, but the absence of coherent prioritization and governance.

Mitigating this risk requires formal experiment prioritization frameworks. Hypotheses can be scored using criteria such as strategic importance, expected value, reversibility, resource intensity, and relevance to critical uncertainties. Such frameworks help ensure that the portfolio of experiments remains aligned with broader strategic priorities rather than drifting toward whatever is easiest to test. In parallel, firms should impose methodological and operational guardrails, including minimum effect-size thresholds, pre-registered success criteria, customer-segment caps, and limits on overlapping tests within the same journey or channel. Automated guardrail systems can further pause or terminate experiments that threaten revenue stability, service reliability, or brand integrity. These mechanisms are especially important in digital settings where experiments can be launched quickly and at scale, sometimes faster than managerial oversight can keep up.

Regular “experiment audits” are another important control mechanism. These audits review whether tests were properly designed, whether data quality standards were met, whether outcome measures were chosen in advance, and whether teams are interpreting results responsibly rather than engaging in selective reporting or p-hacking [3, 11]. Audits also help identify duplication, weak hypotheses, and experiments that continue despite limited strategic

relevance. In this way, organizations preserve the benefits of speed while maintaining managerial control and analytical rigor. The objective is not to slow experimentation unnecessarily, but to ensure that the learning generated is trustworthy, cumulative, and strategically meaningful [3, 11].

Ethical, legal, and interpretive safeguards

A second cluster of risks arises from the data-rich nature of experimentation itself. As organizations collect more granular behavioral data and use algorithms to personalize interventions, experimentation can raise concerns related to privacy, fairness, consent, and accountability. Customers, employees, and regulators may question whether individuals understand how they are being tested, whether particular groups are being disadvantaged, or whether optimization goals are undermining broader stakeholder interests. For this reason, organizations need explicit ethical and legal safeguards built into their experimentation systems rather than treated as afterthoughts. These include ethics review boards, transparent consent mechanisms where appropriate, privacy-by-design principles, and bias-detection algorithms embedded directly into analytics pipelines [19].

Interpretive discipline is equally important. Organizations can become overly reliant on short-term metrics, such as click-through rates, immediate conversions, or short-run engagement, while neglecting long-term customer lifetime value, brand equity, employee wellbeing, or societal impact. A test may appear successful in the near term while quietly eroding trust or creating downstream harms that are not captured in the initial measurement window. Leaders must therefore ensure that experiment evaluation frameworks include both proximal and longer-horizon outcomes. This broadens strategic accountability and reduces the risk that experimentation becomes a tool for narrow optimization rather than sustainable value creation.

Managerial training in causal inference is also essential in this context. Not all observed associations reflect genuine learning, and not all statistically significant results justify strategic action. Managers need the ability to distinguish causal effects from spurious correlations, understand heterogeneity across segments, and recognize the limits of what any single experiment can establish [13]. Without such interpretive competence, experimentation may yield false confidence rather than reliable insight. When properly

governed, however, experimentation can strengthen rather than erode stakeholder trust by making decision processes more transparent, evidence-based, and accountable [19].

From Experimentation to Enduring Competitive Advantage

Firms that institutionalize the Continuous Experimentation Strategy Loop achieve three compounding benefits. First, they dramatically compress the strategy feedback loop. Instead of waiting months for market research updates, quarterly reviews, or post-launch performance summaries, these firms can generate and interpret evidence within days, or even hours in some digital contexts. This enables earlier detection of promising innovations, quicker refinement of weak offerings, and faster abandonment of dead ends before they absorb substantial managerial attention and capital [7, 8, 20]. Speed, in this sense, is not merely operational tempo; it is a structural advantage in organizational learning.

Second, these firms convert uncertainty into a strategic asset. In conventional planning models, uncertainty is often treated primarily as a threat to forecast accuracy and execution discipline. In experimentation-driven firms, uncertainty becomes a source of option value: every ambiguous signal, unexpected behavior, or emerging market shift can be treated as an opportunity for low-cost testing and iterative learning [15, 16]. This fundamentally changes the organization's posture. Rather than defending plans against disruption, firms become more comfortable probing adjacent opportunities, challenging assumptions, and reallocating resources in light of new evidence. The result is greater adaptability under volatile conditions.

Third, institutionalized experimentation strengthens dynamic capabilities — the organizational capacities for sensing opportunities, seizing them through timely action, and reconfiguring assets and processes as environments evolve [10, 14]. These capabilities are difficult for competitors to imitate because they do not depend on a single tool, data set, or innovation method. Instead, they emerge from the cumulative interaction of culture, leadership behavior, incentive systems, governance mechanisms, and learning routines. As experiments accumulate, organizations become better not only at testing ideas but at knowing which questions to ask, where to

search for variation, and how to scale validated insights across units and functions.

In platform markets, these advantages can become especially powerful and self-reinforcing. Successful experiments improve recommendation algorithms, refine personalization systems, increase engagement, and strengthen network effects, thereby generating more data for further experimentation [11, 19]. This recursive cycle deepens the firm's informational advantage, making adaptation progressively faster and more precise. Competitive advantage, therefore, no longer rests solely on superior positioning or efficient execution, but on the ability to build a continuously learning system that evolves with the market.

The result is not merely greater operational efficiency. It is a fundamentally different mode of competing in data-rich environments — one in which strategy is no longer a periodic planning exercise but an ongoing process of disciplined inquiry, rapid feedback, and capability renewal. Firms that master this mode are better equipped not only to survive volatility, but to shape it in ways that less adaptive competitors cannot easily match [10, 14-16].

Conclusion

Digital strategy can no longer be a static artifact updated annually; it must become a living system of continuous experimentation. The framework presented here — hypothesis generation, rapid testing, data-driven learning, iterative decision-making, scaling, and perpetual feedback — offers executives a practical roadmap for replacing prediction with adaptation. Traditional planning's emphasis on control and foresight, once a source of competitive advantage, now creates dangerous rigidity in volatile, data-abundant markets. By contrast, organizations that embed experimentation as their central strategic logic gain superior responsiveness, accelerated innovation, and resilient advantage.

Implementing this shift requires deliberate investment in structures, technology, culture, and risk governance. The journey is neither quick nor risk-free, yet the alternatives — clinging to outdated planning rituals or experimenting chaotically — are worse. Managers who embrace continuous experimentation do not merely optimize existing strategies; they continuously renew the strategy itself. In the data-rich business environments of the coming decade,

the ability to learn faster than competitors will separate enduring winners from those disrupted by their own outdated plans. The Continuous Experimentation Strategy Loop is therefore not a tactical add-on but the new foundation of digital strategic management.

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References

Fagerholm F, Sanchez Guinea A, Mäenpää H, Münch J. The RIGHT model for continuous experimentation. *J Syst Softw.* 2017;123:292-305.

<https://doi.org/10.1016/j.jss.2016.11.001>.

Yaman SG, Munezero M, Münch J, Fagerholm F, Syd O, Aaltola M, et al. Introducing continuous experimentation in large software-intensive product and service organisations. *J Syst Softw.* 2017;133:195-211.

<https://doi.org/10.1016/j.jss.2017.07.042>.

Fabijan A, Dmitriev P, McFarland C, Vermeer L, Holmström Olsson H, Bosch J. Experimentation growth: Evolving trustworthy A/B testing capabilities in online software companies. *J Softw Evol Process.* 2018;30(12):e2113.

<https://doi.org/10.1002/smr.2113>.

Drechsler W, Soe R-M. Agile local governments: Experimentation before implementation. *Gov Inf Q.* 2018;35(2):323-35.

<https://doi.org/10.1016/j.giq.2017.12.003>.

Bojovic N, Genet C, Sabatier V. Learning, signaling, and convincing: The role of experimentation in the business modeling process. *Long Range Plann.* 2018;51(1):64-81.

<https://doi.org/10.1016/j.lrp.2016.10.003>.

Bocken N, Snihur Y. Lean Startup and the business model: Experimenting for novelty and impact. *Long Range Plann.* 2020;53(4):101953.

<https://doi.org/10.1016/j.lrp.2019.101884>.

Chanas S, Myers MD, Hess T. Digital transformation strategy making in pre-digital organizations: The case of a financial services provider. *J Strateg Inf Syst.* 2019;28(1):17-33.

<https://doi.org/10.1016/j.jsis.2018.01.002>.

Correani A, De Massis A, Frattini F. Implementing a digital strategy: Learning from the experience of three digital transformation projects. *Calif Manage Rev.* 2020;62(4):37-56.

<https://doi.org/10.1177/0008125620934864>.

Annosi MC, Martini A, Brunetta F. Learning in an agile setting: A multilevel research study on the evolution of organizational routines. *J Bus Res.* 2020;110:554-66.

<https://doi.org/10.1016/j.jbusres.2018.10.039>.

Mikalef P, Islam N, Parida V, Singh H. Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *J Bus Res.*

2023;164:114071.

<https://doi.org/10.1016/j.jbusres.2023.114169>.

Johari R, Li H, Liskovich I, Weintraub GY. Experimental design in two-sided platforms: An analysis of bias. *Manage Sci.* 2022;68(10):7069-89.

<https://doi.org/10.1287/mnsc.2021.4247>.

Aral S, Brynjolfsson E, Gu C, Wang H, Wu DJ. Understanding the returns from integrated enterprise systems: The impacts of agile and phased implementation strategies. *MIS Q.* 2024;48(2):749-74.

Abbasi A, Somanchi S, Kelley K. The critical challenge of using large-scale digital experiment platforms for scientific discovery. *MIS Q.* 2025;49(1):1-28.

Macca LS, Santoro G, Christofi M. Managerial experimental approaches and business model dynamics: a systematic literature review. *Rev Manag Sci.* 2025;19(3):995-1063.

<https://doi.org/10.1007/s11846-025-00886-x>.

Andersen TCK, Aagaard A. Exploring business model innovation in SMEs in a digital context: Organizing search behaviours, experimentation and decision-making. *Creat Innov Manag.* 2022;31(3):420-37.

<https://doi.org/10.1111/caim.12474>.

Ho WR, Tsolakis N, Dawes T, Dora M. A digital strategy development framework for supply chains. *IEEE Trans Eng Manag.* 2022;69(6):3700-15.

<https://doi.org/10.1109/TEM.2021.3078456>.

Van Zeebroeck N, Kretschmer T. Digital "is" strategy: The role of digital technology adoption in strategy renewal. *IEEE Trans Eng Manag.* 2021;69(6):3700-15.

<https://doi.org/10.1109/TEM.2021.3061234>.

Ros R, Bjarnason E, Runeson P. A theory of factors affecting continuous experimentation (FACE). *Empir Softw Eng.* 2024;29(2):21.

<https://doi.org/10.1007/s10664-023-10358-z>.

Rahman HA, Weiss T. The experimental hand: How platform-based experimentation reconfigures worker autonomy. *Acad Manage J.* 2023;66(6):1801-30.

<https://doi.org/10.5465/amj.2022.0638>.

Xu Y, Koivumäki T. Digital business model effectuation: An agile approach. *Comput Hum Behav.* 2019;96:129-39.

<https://doi.org/10.1016/j.chb.2018.08.037>.

Karagiannis D, Buchmann RA, Utz W. The OMILAB Digital Innovation environment: Agile conceptual models to bridge business value with Digital and Physical Twins for Product-Service Systems. *Comput Ind.* 2022;138:103626.

<https://doi.org/10.1016/j.compind.2022.103626>.

Russo D. The agile success model: a mixed-methods study of a large-scale agile transformation. *ACM Trans Softw Eng Methodol.* 2021;31(4):1-38.

<https://doi.org/10.1145/3464938>.

Soe R-M, Drechsler W. Agile local governments: Experimentation before implementation. *Gov Inf Q.* 2018;35(2):323-35.

Schallmo D, Williams CA, Lohse J. Digital strategy — integrated approach and generic options. *Int J Innov Technol Manag.* 2019;16(1):1940005.

<https://doi.org/10.1142/S136391961940005X>.

Gobble MAM. Digital strategy and digital transformation. *Res Technol Manag.* 2018;61(5):66-71.

<https://doi.org/10.1080/08956308.2018.1495969>.

Kontić L, Vidicki Đ. Strategy for digital organization: Testing a measurement tool for digital transformation. *Strateg Manag.* 2018;23(1):29-37.

<https://doi.org/10.5937/StraMan1801029K>.

Christofi M, Lamprinakos G, Nguyen DK. Digital strategy design and digital transformation: a review and future research directions. *Int Mark Rev.* 2025.

<https://doi.org/10.1108/IMR-10-2025-0538>.

Czauderna A, Budke A. How digital strategy and management games can facilitate the practice of dynamic decision-making. *Educ Sci.* 2020;10(4):99.

<https://doi.org/10.3390/educsci10040099>.

Deniz B, Nguyen Q, Sequeira P. Learning from Success and Failure in Digital Experimentation: A Large-Scale Study of A/B Testing Behavior. *MIS Q.* 2025;49(1).

<https://doi.org/10.25300/misq/2025/18201>.