

From Data Abundance to Decision Advantage: A Unified Capability Framework for Empirical Entrepreneurship and Analytics- Enabled Organizations

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Abstract

Organizations increasingly possess sophisticated analytical technologies yet remain unable to convert data abundance into reliable decision advantage. This conceptual paper integrates research on empirical entrepreneurship, big data analytics capability, data quality, data warehousing, stream analytics, text analytics, multi-criteria decision analysis, and clinical decision support. It advances a unified analytics-to-action capability framework comprising five interdependent layers: data readiness, decision architecture, analytical reasoning, organizational activation, and responsible governance. The framework explains why analytics investments produce contingent rather than automatic performance effects and why the same technical capability yields different outcomes across entrepreneurial, commercial, media, logistics, financial, and healthcare settings. Comparative analysis of small-service-firm, Dell, AMC Networks, UPS, streaming-platform, and clinical decision-support contexts demonstrates that value is created when analytical outputs are timely, decision-relevant, interpretable, and embedded in accountable workflows. Four propositions specify how complementarity among the five layers influences decision quality, organizational agility, and sustained value realization. The analysis also identifies failure modes, including fragmented data, analytics theater, metric gaming, model drift, surveillance concerns, and inequitable automation. The paper contributes to ongoing scholarship by connecting entrepreneurial experimentation with enterprise analytics as a shared learning mechanism and by positioning governance as a productive capability that protects legitimacy while improving the reliability of organizational learning. A research agenda is offered for multilevel, longitudinal, and comparative testing of the framework.

Keywords: analytics capability; big data; business intelligence; decision intelligence; empirical entrepreneurship; data governance; organizational learning

Introduction

Data-intensive technologies have changed both the practice of entrepreneurship and the operating logic of established organizations. Digital transactions, sensors, platforms, social media, and enterprise systems continuously produce behavioral traces that can be used to identify opportunities, test assumptions, coordinate resources, and automate decisions. Yet the availability of data does not itself constitute knowledge, and analytical sophistication does not guarantee organizational value. Empirical studies consistently show that performance effects depend on complementary organizational resources, managerial capabilities, and the contexts in which analytics is used (Gupta & George, 2016; Mikalef et al., 2019; Müller et al., 2018; Wamba et al., 2017). This contingency is the central problem addressed in this paper.

The source material synthesized here spans seemingly different domains: entrepreneurial experimentation, data readiness, data warehousing and scorecards, customer analytics at Dell and AMC Networks, stream processing, multi-goal decision analysis, and clinical decision support. Treated separately, these topics appear to represent different tools and industries. Integrated analytically, however, they reveal one underlying question: Under what conditions does data become a defensible decision advantage? This question matters because organizations frequently invest in infrastructure and dashboards without redesigning decisions, clarifying accountability, or protecting the people represented in the data. The result may be faster reporting without better judgment, more metrics without strategic coherence, or automated recommendations without legitimacy.

This conceptual paper develops an analytics-to-action capability framework that connects five interdependent layers: data readiness, decision architecture, analytical reasoning, organizational activation, and responsible governance. The framework extends research on strategic value creation from big data analytics by specifying the decision pathway through which technical and human resources become organizational learning and action (Grover et al., 2018). It also connects empirical entrepreneurship with enterprise analytics. Both are organized forms of disciplined learning: assumptions are translated into measurable propositions, evidence is generated or observed, alternatives are evaluated, and decisions are revised. The difference is primarily one of scale, latency, and institutional consequence.

The paper makes three contributions. First, it reframes empirical entrepreneurship and business analytics as manifestations of a common evidence-based learning capability. Second, it explains value realization through complementarity among technical, analytical, organizational, and governance resources rather than through technology adoption alone. Third, it articulates research propositions and a future research agenda that can be tested across firm sizes, industries, and decision stakes. The discussion begins by establishing the theoretical foundations of empirical learning and dynamic analytics capability, then develops the five-layer framework, applies it comparatively, and examines implications for scholarship and practice.

Empirical Entrepreneurship as a Logic of Organizational Learning

Empirical entrepreneurship replaces unexamined founder intuition with disciplined inference from observable market behavior. Intuition remains relevant for generating hypotheses, but evidence is used to challenge opportunity beliefs, refine business models, and redirect scarce resources. For technology-based firms operating across borders, the business model configures value creation, delivery, and capture; empirical testing allows each configuration to be revised as market evidence accumulates (Onetti et al., 2012). The economic consequence is potentially improved capital allocation because ventures can terminate weak assumptions earlier and direct resources toward validated customer problems. The technological consequence is an accelerated feedback cycle in which digital infrastructures both enable experimentation and generate the data used to evaluate it.

This logic should not be romanticized as neutral or automatically causal. Observational data may reproduce selection effects, platform designs may determine which behavior becomes visible, and short-term conversion metrics may crowd out long-term customer or social value. George et al. (2016) cautioned that big data methods create methodological opportunities while also demanding theoretical discipline. Consequently, empirical entrepreneurship is strongest when experimentation distinguishes prediction from causal inference, specifies meaningful outcomes in advance, and recognizes that evidence is generated within a social and technological system.

The same learning logic applies in established firms. Dell's effort to integrate digital customer signals with sales and marketing information, AMC Networks' attempt to connect fragmented audience behavior across channels, and a small service firm's use of booking and point-of-sale data all involve cycles of sensing, interpretation, experimentation, and reconfiguration. These cycles resemble dynamic capabilities because they allow organizations to sense changes, seize opportunities, and transform processes. Research on big data analytics capability similarly emphasizes that tangible technology, human expertise, and intangible organizational resources must be combined rather than acquired independently (Gupta & George, 2016).

A useful synthesis therefore treats analytics not as a collection of tools but as an organizational learning system. Data make events observable; architectures make observations accessible; analytical methods turn observations into claims; organizational routines turn claims into action; and governance determines whether those actions remain reliable, fair, and legitimate. A weakness at any layer can interrupt the pathway.

The Analytics-to-Action Capability Framework

The proposed framework contains five layers that are analytically distinct but operationally interdependent. It is deliberately technology-agnostic: a small firm using integrated spreadsheets and a global enterprise using cloud-scale streaming infrastructure can possess the same underlying capabilities at different levels of maturity. What matters is fit between the decision, the data, the analytical method, the workflow, and the consequences of error.

Layer 1: Data Readiness

Data readiness is the degree to which information is fit for a specified analytical and decision purpose. It includes accuracy, completeness, consistency, timeliness, relevance, representational integrity, and traceability. Wang and Strong's (1996) consumer-oriented account established that data quality extends beyond accuracy, while Pipino et al. (2002) showed the need to combine objective assessment with contextual evaluation. These insights are especially important in contemporary analytics because technically valid models can produce strategically invalid conclusions when definitions, populations, timestamps, or missingness mechanisms are misunderstood.

Readiness should therefore be evaluated against a decision contract rather than a generic quality score. The contract identifies the decision owner, unit of analysis, target outcome, acceptable latency, relevant population, period of validity, and consequences of false positive and false negative errors. A seasonal-demand forecast, for example, requires consistent product and service definitions, aligned timestamps, sufficient history, documentation of promotions and stockouts, and a process for detecting structural breaks. A customer-retention model additionally requires a defensible definition of churn and safeguards against using protected or proxy attributes inappropriately.

This layer makes data provenance and representativeness central. Data that are complete within an operational system may still exclude customers who could not access that system. In an entrepreneurial experiment, click-through rates may capture interface response but not durable customer value. In clinical decision support, electronic health record data may encode unequal access, documentation practices, and prior treatment decisions. Readiness therefore includes social validity: whether the data-generating process adequately represents the people and processes about which the organization intends to decide.

Layer 2: Decision Architecture

Decision architecture comprises the technical and semantic arrangements that deliver decision-ready information at the required scale and speed. Traditional data warehouses created conformed dimensions and separated analytical workloads from transaction processing. Contemporary architectures increasingly combine governed warehouse functions with flexible data-lake storage, distributed processing, and event streams. The managerial principle is not that every organization needs a particular architecture, but that integration, metadata, lineage, access control, and latency must match the decision.

The progression from periodic reporting to streaming illustrates this contingency. Batch analysis remains appropriate for strategic planning, model development, and decisions whose value does not deteriorate rapidly. Stream analytics becomes valuable when delay itself carries economic or social cost, such as fraud authorization, vehicle dispatch, service reliability, or clinical deterioration. Digital data streams can create value by embedding sensing and response directly into operations (Pigni et al., 2016). However, unbounded and out-of-order events introduce trade-offs among correctness, latency, and cost, making event-time semantics, state management, and failure recovery part of decision quality rather than merely engineering concerns (Akida et al., 2015).

Warehousing also supports strategic coherence when it supplies comparable indicators to performance-management systems. The Balanced Scorecard broadened evaluation beyond financial results to customer, internal-process, and learning-and-growth perspectives (Kaplan & Norton, 1992). Its value depends on a measurement backbone that provides consistent definitions across units. A warehouse cannot establish valid causal relationships among scorecard measures, however, and a scorecard cannot repair poor source data. Their complementarity is therefore conditional on explicit strategy maps, auditable definitions, and managerial review.

Layer 3: Analytical Reasoning

Analytical reasoning is the disciplined selection, validation, interpretation, and communication of methods appropriate to a decision. Descriptive reporting answers what occurred; diagnostic analysis investigates why; predictive modeling estimates what may occur; prescriptive analysis evaluates what should be done under specified objectives and constraints.

Visual analytics supports interactive discovery and hypothesis refinement, whereas business reporting communicates stable measures and conclusions to accountable audiences. Predictive visual analytics is especially valuable when decision makers must examine patterns, uncertainty, and model behavior rather than accept a single score (Lu et al., 2017).

Method choice must follow the decision rather than technological fashion. Regression and time-series methods may support demand forecasting; classification and survival models can estimate conversion or retention; clustering can support exploratory segmentation; natural language processing can extract entities, themes, intent, and sentiment from unstructured discourse; causal inference and uplift modeling can estimate incremental intervention effects; and optimization or simulation can evaluate constrained choices. Each method answers a different question and carries different assumptions.

Multi-goal decisions illustrate why interpretation cannot be automated away. A single-goal problem can optimize one scalar objective subject to constraints. A multi-criteria problem contains objectives that may conflict, use different units, and embody stakeholder values. Methods such as multi-attribute value analysis and the analytic hierarchy process make trade-offs explicit (Keeney & Raiffa, 1993; Saaty, 1990). Yet weights are not objective facts. They are governance choices that require sensitivity analysis, stakeholder deliberation, and examination of Pareto-efficient alternatives. Analytical rigor in such settings means revealing rather than concealing value judgments.

Layer 4: Organizational Activation

Organizational activation is the conversion of analytical claims into changed decisions, routines, and resource allocations. It requires leadership sponsorship, domain expertise, clear decision rights, analytical literacy, incentives for learning, and feedback on realized outcomes. This layer explains why similar technologies generate different results. Wamba et al. (2017) found that dynamic capabilities mediate the relationship between big data analytics and performance, while Mikalef et al. (2019) demonstrated that resource orchestration matters alongside technical assets.

Activation is visible when an analytical output changes who acts, when action occurs, and how results are reviewed. A dashboard viewed without an accountable decision is reporting, not activation. A predictive score that does not fit workflow is a technical artifact, not a capability. Conversely, a modest forecasting model embedded in staffing, inventory, and post-decision review can generate substantial value. This distinction is particularly consequential for small organizations, where analytical ownership competes with daily operations and reliance on vendors may weaken internal learning.

Resistance should not be reduced to irrational opposition. Employees may reasonably resist analytics perceived as surveillance, a threat to professional judgment, or a mechanism for imposing decontextualized performance targets. Activation therefore requires participation in design, understandable explanations, opportunities to contest data, and safeguards against metric misuse. These are not peripheral change-management activities; they affect data quality, adoption, and the validity of feedback received after deployment.

Layer 5: Responsible Governance

Responsible governance establishes the rules, controls, and accountability relationships that keep analytics reliable and legitimate over time. It includes data stewardship, privacy and security, model validation, bias assessment, human oversight, documentation, auditability, incident response, and retirement criteria. Governance is often framed as a constraint on innovation. In the proposed framework, it is productive infrastructure because it makes trustworthy experimentation and scalable reuse possible.

The need intensifies as analytical decisions become faster, more automated, and more consequential. Text and sentiment models can misread context, irony, dialect, or multilingual discourse. Predictive models can drift as populations and behavior change. Optimization can efficiently reproduce an incomplete objective function. Performance indicators can be gamed when rewards are tied to measures. Governance responds by specifying intended use, validating local performance, monitoring distributional effects, and assigning responsibility for intervention.

Privacy is especially salient when data are granular enough to link behavior across contexts. The ethical question is not limited to legal permission; it includes proportionality, purpose limitation, and whether individuals can reasonably anticipate how their data will shape decisions. Big data can also amplify institutional asymmetries when organizations possess greater capacity than affected communities to define categories and uses (Taylor & Schroeder, 2015). In healthcare, implementation reviews identify trust, workflow fit, transparency, and organizational conditions as persistent determinants of adoption (Abell et al., 2023; Hassan et al., 2024). Governance that preserves meaningful human judgment and supplies avenues for redress can therefore improve both legitimacy and practical use.

Capability Complementarity and Propositions

The framework's principal claim is complementarity. Investment in one layer has diminishing value when adjacent layers remain weak. High-quality data cannot compensate for an irrelevant decision objective; sophisticated models cannot compensate for fragmented workflows; strong adoption cannot legitimize biased data; and restrictive governance that is disconnected from operations can suppress learning without reducing risk.

Proposition 1: The positive relationship between analytical technology investment and decision quality is strengthened by complementarity among data readiness, decision architecture, and analytical reasoning.

Proposition 2: Organizational activation mediates the relationship between analytical insight quality and realized operational or strategic performance.

Proposition 3: Responsible governance positively moderates the relationship between analytics use and sustained value realization by reducing model, privacy, fairness, and legitimacy failures.

Proposition 4: The performance value of low-latency analytics increases with the rate at which decision value decays, but only when error costs, escalation rules, and human oversight are explicitly designed.

These propositions refine the frequent assertion that analytics improves performance. They predict that direct technology-performance effects will be unstable across contexts because the operative unit is a capability configuration. They also imply equifinality: organizations may reach high performance through different configurations. A small service firm may use modest technology with strong process integration, while a platform company may require streaming infrastructure and automated controls. Both can be analytically mature relative to their decisions.

Comparative Applications Across Organizational Contexts

Small Service-Firm Analytics and Empirical Experimentation

For a service business such as Limitless Pets, big data should be defined by decision complexity rather than petabyte scale. Booking records, point-of-sale transactions, service duration, inventory, staffing, reviews, and customer rebooking behavior form a high-variety operational dataset. Integrated carefully, these data can support demand forecasting, appointment-capacity planning, customer retention, service-quality analysis, and inventory optimization.

The framework prevents premature sophistication. Data readiness begins with stable customer identifiers, service definitions, timestamps, and documentation of cancellations or promotions. Decision architecture may consist of governed exports and a reproducible analytical dataset rather than an enterprise platform. Analytical reasoning could combine seasonal forecasts with logistic retention models and controlled tests of reminder cadence or service bundles. Activation occurs when forecasts modify staffing and purchasing decisions. Governance requires role-based access, retention rules, fair use of employee measures, and explicit limits on personalization.

The entrepreneurial contribution is the learning cycle. A promotion should be treated as a hypothesis with a prespecified outcome, comparison condition, time horizon, and stop rule. This reduces the risk of interpreting ordinary variation as success. It also converts vendor dashboards from unquestioned authorities into evidence sources whose definitions and limitations can be examined.

Enterprise Customer and Audience Analytics: Dell and AMC Networks

The Dell and AMC Networks cases reported by Sharda et al. (2024) demonstrate the same capability problem at enterprise scale.

Dell confronted fragmented customer signals and a B2B journey in which buyers conducted substantial digital research before sales contact. Integrating structured enterprise records with clickstream and social information created opportunities for segmentation, lead scoring, journey analysis, personalization, and marketing attribution. AMC confronted fragmented viewing across linear, streaming, retail, and social channels, making single-source ratings increasingly incomplete.

In both cases, architecture created the possibility of insight, but method and activation determined value. Dell's analytical workbench supported faster experimentation and a more coherent view of customer behavior. AMC's integrated environment enabled audience segmentation, ratings prediction, promotion analysis, and advertiser insight. Text analytics added themes, entities, intent, and sentiment from reviews or social discourse. Research shows that text analytics can support organizational sense-making and customer agility when language is converted into decision-relevant constructs rather than treated as an undifferentiated sentiment score (Abbasi et al., 2018; Zhou et al., 2018).

The cases also reveal attribution and governance risks. Multichannel revenue cannot be credibly assigned to one touchpoint without defensible counterfactual assumptions. Identity resolution may improve personalization while increasing privacy exposure. Sentiment models can systematically underperform on communities whose language differs from training data. Accordingly, enterprise customer analytics requires experimentation, local validation, consent and purpose controls, and ongoing checks for model drift.

Global Logistics, Warehousing, and Performance Coherence

Global logistics organizations illustrate the need to connect enterprise data architecture with operational and strategic measurement. Route events, package scans, telematics, customer commitments, labor conditions, safety incidents, and costs must be reconciled across locations. Warehousing supplies consistent dimensions and historical context, while streaming supports exceptions whose value decays quickly. The Balanced Scorecard can connect financial outcomes with customer reliability, internal process performance, and workforce learning, but only if the indicators are few, strategically linked, and comparable.

This application exposes the danger of analytics theater. A global dashboard may display consistent colors while concealing inconsistent definitions or delayed data. Units may optimize a score rather than the underlying service outcome. A stronger design pairs each key indicator with an owner, decision cadence, lineage record, leading or lagging status, threshold rationale, and review of unintended effects. Streaming exceptions should trigger predefined escalation, whereas long-horizon network design should rely on deeper batch analysis and simulation. Hybrid analytical rhythms are therefore more valuable than universal real-time processing.

Stream Analytics in Mobility, Media, and Financial Services

Mobility platforms, streaming media, and financial services have been prominent users of stream analytics because they share high event velocity, rapid decay of decision value, embedded automation, and stringent reliability requirements. Rider-driver matching, playback quality intervention, transaction authorization, and fraud scoring lose much of their value if delayed. These industries therefore operationalize analytics within the process rather than after it.

Stream analytics will generate more use cases as digital operations proliferate, but it will not replace batch analytics. Real-time features still require historical training data, retrospective evaluation, and governance. The strongest design is a closed loop: batch environments support model development and strategic analysis; streaming environments apply models and capture outcomes; monitoring identifies drift and failures; and periodic review recalibrates both model and decision policy. Correctness, latency, and cost remain explicit trade-offs rather than engineering details (Akidau et al., 2015).

High-Stakes Analytics: Clinical Decision Support

Clinical decision support demonstrates why technical performance is insufficient for adoption. Diagnostic and treatment recommendations enter workflows characterized by time pressure, incomplete information, professional accountability, and asymmetric consequences. Physicians may reject tools that create alert fatigue, obscure uncertainty, conflict with local knowledge, or increase documentation burden. Systematic reviews identify workflow integration, perceived usefulness, trust, organizational support, and clinician involvement as recurring barriers and facilitators (Abell et al., 2023; Hassan et al., 2024).

The five-layer framework suggests a safer implementation pathway. Data readiness requires local assessment of completeness, coding, representativeness, and subgroup performance. Decision architecture must integrate with the clinical workflow at the appropriate moment. Analytical reasoning must communicate uncertainty, intended use, and alternatives. Organizational activation should use clinician co-design, champions, training, and audit-and-feedback strategies, consistent with implementation research (Powell et al., 2012). Responsible governance must specify accountability, override procedures, privacy protection, bias monitoring, incident review, and model retirement.

Importantly, increasing use should not be the primary objective. Appropriate use and improved patient outcomes are stronger criteria. Mandatory utilization can create automation bias or superficial compliance. Administrators should instead begin with narrowly defined, high-value decisions, conduct prospective local evaluation, preserve clinician judgment, and disclose performance limitations. This approach treats adoption as an outcome of trustworthy fit rather than a target imposed independently of safety.

Multi-Goal Decision Analysis and Risk Mitigation

Analytics-enabled organizations frequently face decisions that cannot be reduced to one objective. A hospital selecting a patient-transport network, for example, may seek to minimize cost, maximize on-time arrival, expand service to underserved communities, reduce safety incidents, and maintain resilience during severe weather. These criteria conflict and are measured in different units. Treating them as one weighted score without deliberation may disguise ethical and strategic choices.

A defensible process first separates nonnegotiable constraints from trade-off criteria. Regulatory compliance and maximum safety thresholds may be constraints; cost, timeliness, equity coverage, and resilience may remain objectives. Stakeholders then define performance scales and express preferences, after which multiple methods and scenarios can be compared. Sensitivity analysis should identify how changes in weights, thresholds, missing data, and storm assumptions alter the preferred option. Pareto analysis can show alternatives that are not dominated, preventing false claims that one option is universally optimal.

Risk mitigation becomes a system rather than a one-time score. Contract provisions, redundancy, service-level thresholds, monitoring, and contingency triggers manage uncertainty after selection. Interactive visualizations can help stakeholders inspect trade-offs, but visual clarity must not be mistaken for epistemic certainty. The legitimacy of the decision depends on documenting whose preferences were included, how equity was operationalized, and which residual risks were accepted.

Cross-Cutting Failure Modes

Several failure modes recur across the applications. First, fragmented data and inconsistent definitions produce spurious precision. Second, analytics theater occurs when visually impressive outputs are disconnected from decision accountability or outcome evaluation. Third, measurement pressure can encourage gaming, reduce psychological safety, and turn learning systems into surveillance systems. Fourth, model drift erodes reliability as customers, markets, language, or clinical populations change. Fifth, automation can scale inequity when historical data reflect unequal opportunity or service.

These failures are mutually reinforcing. Poor data quality weakens trust; weak trust reduces adoption; low adoption alters the data generated after implementation; and the resulting feedback can be misread as model failure or employee resistance. Governance must therefore be adaptive and socio-technical. It should combine quantitative monitoring with qualitative feedback from people who use and are affected by the system.

Firm size changes the expression of these risks. Small firms face limited expertise, fragmented vendor tools, and short payback horizons. Medium-sized firms face cross-functional standardization and talent retention. Large firms face legacy systems, political disputes over metric ownership, cybersecurity exposure, and model-governance complexity. The appropriate control environment should be proportionate, but no organization is too small for clear data ownership, privacy safeguards, metric definitions, and post-decision review.

Implications for Theory

The framework contributes to analytics capability research by locating value creation in a sequence of linked transformations: observation, accessibility, inference, action, and governed learning.

Existing capability studies establish that technological, human, and intangible resources jointly influence performance (Gupta & George, 2016; Mikalef et al., 2019). The present synthesis adds decision specificity. A resource becomes valuable not merely because it supports analytics generally, but because it improves a consequential decision at acceptable cost and risk.

The framework also links empirical entrepreneurship to organizational learning and dynamic capabilities. Entrepreneurial experimentation and enterprise analytics differ less in logic than commonly assumed. Both depend on hypothesis quality, valid evidence, rapid feedback, and willingness to revise routines. This connection suggests that empirical entrepreneurship can be studied not only at venture formation but also as a repeatable microfoundation of organizational adaptation.

Finally, responsible governance is theorized as complementary rather than antagonistic to innovation. Clear intended-use boundaries, provenance, monitoring, and accountability can reduce uncertainty and enable reuse. Governance may therefore have a curvilinear effect: inadequate governance increases failure and distrust, while excessively detached or rigid governance delays learning. The research opportunity is to identify configurations that are sufficiently protective and sufficiently adaptive for different decision stakes.

Managerial Implications

Managers should begin analytics initiatives with a decision portfolio, not a tool inventory. Each initiative should identify the decision owner, current process, target outcome, data requirements, acceptable latency, error costs, affected stakeholders, intervention pathway, and review cadence. This decision contract makes it possible to distinguish useful infrastructure from unnecessary complexity.

Organizations should also manage analytics as a learning portfolio. Some initiatives will produce direct financial returns; others will reduce risk, improve access, strengthen service quality, or build reusable data assets. A balanced evaluation should include outcome improvement, adoption quality, distributional effects, and learning generated. Projects that do not change a decision or improve a validated outcome should be redesigned or retired.

Leadership should protect the conditions for truthful feedback. Employees need safe channels to report data problems, contest metrics, and document exceptions. Model owners need authority to pause systems when drift or harm appears. Decision makers should receive uncertainty and limitations alongside recommendations. These practices prevent confidence theater and make analytics more, not less, actionable.

Limitations

This paper is a conceptual synthesis rather than a systematic review or empirical test. The organizational cases are illustrative and are used to examine mechanisms, not to establish causal effects or comparative performance rankings. Some rapidly evolving architectural practices are represented at the level of managerial principle rather than platform-specific implementation. The proposed layers may also interact recursively rather than sequentially; for example, organizational resistance may reveal data-quality defects, and governance incidents may prompt architectural redesign.

These limitations define opportunities for empirical refinement. Measures of each layer must be decision-specific and should distinguish formal policies from enacted routines. Research should also test boundary conditions, including environmental turbulence, regulation, decision reversibility, organizational size, and the severity and distribution of error costs.

Conclusion

Data abundance becomes decision advantage only through an integrated organizational capability. Empirical entrepreneurship supplies a logic of disciplined learning, while business intelligence, data warehousing, statistical modeling, text analytics, stream processing, and prescriptive methods provide different mechanisms for operationalizing that logic. Their value is contingent on whether data are fit for purpose, architectures match decision latency, methods support valid inference, workflows convert insight into action, and governance preserves reliability and legitimacy.

The five-layer analytics-to-action framework explains why technology-centered initiatives so often disappoint and why modest analytical systems can create substantial value when embedded well.

Across a small service business, global customer and media analytics, logistics, financial streams, and clinical decision support, the decisive issue is not the volume of data or sophistication of the model. It is the quality of the learning system built around the decision.

For scholarship, the framework offers testable propositions concerning capability complementarity, organizational activation, responsible governance, and the economics of latency. For practice, it offers a disciplined sequence from decision contract to post-decision review. The broader implication is consequential: responsible governance and human judgment are not obstacles to analytical performance. Properly designed, they are capabilities that allow organizations to learn faster without sacrificing fairness, trust, or accountability.

Table 1
Analytics-to-Action Capability Framework

Layer	Core question	Representative mechanisms	Primary failure risk
Data readiness	Are the data fit for this decision?	Quality, provenance, representativeness, definitions	Spurious precision
Decision architecture	Can evidence reach the decision at the needed scale and speed?	Integration, warehouse, event streams, metadata, lineage	Fragmentation or latency mismatch
Analytical reasoning	Does the method support the claim being made?	Statistics, visualization, prediction, causal inference, optimization	Method–question mismatch
Organizational activation	Will insight change an accountable decision or routine?	Decision rights, workflow fit, literacy, incentives, feedback	Analytics theater or resistance
Responsible governance	Can the system remain trustworthy and legitimate?	Privacy, security, validation, fairness, monitoring, redress	Drift, harm, or loss of trust

References

- Abbasi, A., Zhou, Y., Deng, S., & Zhang, P. (2018). Text analytics to support sense-making in social media: A language-action perspective. *MIS Quarterly*, 42(2), 427–464. <https://doi.org/10.25300/MISQ/2018/13239>
- Abell, B., Naicker, S., Rodwell, D., Donovan, T., Tariq, A., Baysari, M., Blythe, R., Parsons, R., & McPhail, S. M. (2023). Identifying barriers and facilitators to successful implementation of computerized clinical decision support systems in hospitals: A NASSS framework-informed scoping review. *Implementation Science*, 18, Article 32. <https://doi.org/10.1186/s13012-023-01287-y>
- Akidau, T., Bradshaw, R., Chambers, C., Chernyak, S., Fernández-Moctezuma, R. J., Lax, R., McVeety, S., Mills, D., Perry, F., Schmidt, E., & Whittle, S. (2015). The Dataflow model: A practical approach to balancing correctness, latency, and cost in massive-scale, unbounded, out-of-order data processing. *Proceedings of the VLDB Endowment*, 8(12), 1792–1803. <https://doi.org/10.14778/2824032.2824076>
- George, G., Osinga, E. C., Lavie, D., & Scott, B. A. (2016). Big data and data science methods for management research. *Academy of Management Journal*, 59(5), 1493–1507. <https://doi.org/10.5465/amj.2016.4005>
- Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems*, 35(2), 388–423. <https://doi.org/10.1080/07421222.2018.1451951>
- Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, 53(8), 1049–1064. <https://doi.org/10.1016/j.im.2016.07.004>
- Hassan, M., Kushniruk, A., & Borycki, E. (2024). Barriers to and facilitators of artificial intelligence adoption in health care: Scoping review. *JMIR Human Factors*, 11, e48633. <https://doi.org/10.2196/48633>

- Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard—Measures that drive performance. *Harvard Business Review*, 70(1), 71–79.
- Keeney, R. L., & Raiffa, H. (1993). *Decisions with multiple objectives: Preferences and value tradeoffs*. Cambridge University Press.
- Lu, Y., Garcia, R., Hansen, B., Gleicher, M., & Maciejewski, R. (2017). The state-of-the-art in predictive visual analytics. *Computer Graphics Forum*, 36(3), 539–562. <https://doi.org/10.1111/cgf.13204>
- Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, 98, 261–276. <https://doi.org/10.1016/j.jbusres.2019.01.044>
- Müller, O., Fay, M., & vom Brocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems*, 35(2), 488–509. <https://doi.org/10.1080/07421222.2018.1451955>
- Onetti, A., Zucchella, A., Jones, M. V., & McDougall-Covin, P. P. (2012). Internationalization, innovation and entrepreneurship: Business models for new technology-based firms. *Journal of Management & Governance*, 16(3), 337–368. <https://doi.org/10.1007/s10997-010-9154-1>
- Pigni, F., Piccoli, G., & Watson, R. T. (2016). Digital data streams: Creating value from the real-time flow of big data. *California Management Review*, 58(3), 5–25. <https://doi.org/10.1525/cmr.2016.58.3.5>
- Pipino, L. L., Lee, Y. W., & Wang, R. Y. (2002). Data quality assessment. *Communications of the ACM*, 45(4), 211–218. <https://doi.org/10.1145/505248.506010>
- Powell, B. J., McMillen, J. C., Proctor, E. K., Carpenter, C. R., Griffey, R. T., Bunger, A. C., Glass, J. E., & York, J. L. (2012). A compilation of strategies for implementing clinical innovations in health and mental health. *Medical Care Research and Review*, 69(2), 123–157. <https://doi.org/10.1177/1077558711430690>
- Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, 48(1), 9–26. [https://doi.org/10.1016/0377-2217\(90\)90057-I](https://doi.org/10.1016/0377-2217(90)90057-I)
- Sharda, R., Delen, D., & Turban, E. (2024). *Business intelligence, analytics, data science, and AI: A managerial perspective* (5th ed.). Pearson.
- Taylor, L., & Schroeder, R. (2015). Is bigger better? The emergence of big data as a tool for international development policy. *GeoJournal*, 80(4), 503–518. <https://doi.org/10.1007/s10708-014-9603-5>
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, 12(4), 5–33. <https://doi.org/10.1080/07421222.1996.11518099>
- Zhou, S., Qiao, Z., Du, Q., Wang, G. A., Fan, W., & Yan, X. (2018). Measuring customer agility from online reviews using big data text analytics. *Journal of Management Information Systems*, 35(2), 510–539. <https://doi.org/10.1080/07421222.2018.1451956>