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The Data-to-Business-Value Conversion Model: Linking Analytics Capability, Managerial Interpretation, and Competitive Advantage

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Abstract

Firms increasingly invest in data infrastructure, analytics tools, digital platforms, and specialist talent in the expectation that these resources will improve decision quality, operational effectiveness, innovation, and market performance. Yet the relationship between analytics investment and business value remains uneven, because data availability does not automatically generate strategic action. This article addresses the persistent data-to-value challenge by examining why analytics capability often remains under-converted into realized business outcomes.

The central problem is that prior research has frequently examined analytics capability, decision-making, and business value as related but insufficiently integrated domains. Analytics capability explains what firms can potentially know, while business value explains what firms ultimately gain, but the conversion mechanism between the two is often underdeveloped. This article argues that managerial interpretation is the missing link that determines whether analytical outputs become meaningful, trusted, and actionable.

The objective of this article is to develop a new conceptual model, the Data-to-Business-Value Conversion Model. The model links analytics capability to business value and competitive advantage through managerial interpretation as the central mediating mechanism. It explains how firms move from data resources and analytical outputs to decisions, organizational actions, value creation, and strategic advantage.

The proposed model identifies four connected elements: data and analytics capability, managerial interpretation, business value creation mechanisms, and competitive advantage pathways. It shows that analytics capability provides decision potential, managerial interpretation converts that potential into action, business value emerges through organizational mechanisms, and competitive advantage depends on whether value is embedded in difficult-to-imitate routines. The article contributes a testable framework for future research and a practical logic for managers seeking to improve analytics value conversion.

Keywords Competitive advantage, Data-driven decision-making, Data analytics capability, Managerial interpretation, Business value, Conceptual model

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Introduction

The growth of data-intensive competition has encouraged firms to treat analytics capability as a central source of

strategic renewal, operational improvement, and performance differentiation. Research on big data analytics has shown that firms can benefit from data infrastructure, analytical tools, and organizational capabilities when these resources are aligned with dynamic capabilities and business processes [1]. However, the persistence of uneven returns indicates that analytics capability is not a self-executing source of value, because data must still be interpreted, prioritized, and translated into managerial action.

The data-to-value problem arises because firms often confuse analytical availability with strategic usefulness. Studies of big data value realization show that organizations must move beyond data accumulation toward deliberate processes of extracting, interpreting, and applying insights in specific business contexts [2]. This distinction is important because large volumes of data can increase analytical complexity rather than improve decisions when firms lack the interpretive and organizational capacity to make sense of analytical outputs [3].

Existing research has made substantial progress in explaining the performance effects of analytics capability, but it often leaves the interpretive conversion stage implicit. For example, information technology-enabled dynamic capabilities and analytics capabilities have been linked to competitive performance, yet these relationships frequently depend on intermediate organizational processes that shape how insights are used [4, 5]. This article therefore conceptualizes managerial interpretation as the cognitive, social, and strategic mechanism through which analytics capability becomes actionable business knowledge.

The purpose of this article is to develop the Data-to-Business-Value Conversion Model as an original conceptual framework linking analytics capability, managerial interpretation, business value creation, and competitive advantage. The model builds on evidence that analytics can affect firm performance directly and indirectly, but it argues that the decisive conversion point lies in how managers evaluate analytical outputs, reconcile them with contextual knowledge, and commit organizational resources [6, 7]. In this view, data becomes valuable not simply because it is processed, but because it is interpreted within decision processes that guide action.

Data and Analytics Capability in Digital Firms

Data and analytics capability refers to a firm's capacity to collect, integrate, process, analyze, and deploy data in ways that support organizational decision-making and strategic action. Prior research defines this capability as multidimensional, combining technological infrastructure, analytical talent, data governance, managerial support, and organizational culture [7]. The capability is therefore not limited to software or technical tools, because business value depends on the integration of data resources with human expertise and organizational routines.

Empirical research has shown that analytics capability can improve organizational outcomes, but the effects are often indirect and contingent. In healthcare and other data-intensive sectors, analytics capability enables better coordination, evidence-based decisions, and potential performance improvement when supported by organizational readiness and domain-specific processes [8]. Similarly, studies of high-value business performance indicate that analytics contributes to value when firms possess the managerial and organizational conditions needed to use insights effectively [9].

Analytics capability also matters because it creates a structured input for value conversion. Investments in analytics can influence firm performance through mediating mechanisms such as process improvement, operational responsiveness, and business process performance [10, 11]. This evidence supports the view that analytics capability should be treated as a foundational antecedent in the conversion model, rather than as a direct and automatic source of business value.

Table 1 defines the core dimensions and components of data and analytics capability. These dimensions synthesize the technological, human, cultural, and process-based foundations that enable firms to generate analytical insight and prepare it for managerial interpretation [12, 13]. By separating capability components from value outcomes, the table clarifies that analytics capability creates potential for decision improvement, while the realization of that potential depends on subsequent interpretive and organizational mechanisms.

Table 1. Data and Analytics Capability Dimensions: Infrastructure, Talent, Culture, and Process Enablers

Capability dimension	Core components	Conversion role	Expected limitation if weak
Data infrastructure	Data platforms, databases, integration systems, data quality mechanisms	Enables reliable access to timely and usable data	Fragmented or poor-quality data limits insight credibility
Analytical tools	Statistical models, business intelligence systems, predictive analytics, visualization tools	Converts raw data into analytical outputs and decision signals	Outputs remain descriptive, delayed, or insufficiently actionable
Human analytical talent	Data scientists, analysts, domain experts, analytics translators	Connects technical analysis with business problems	Analytical results may not match managerial or strategic needs
Data-driven culture	Evidence orientation, openness to analytics, learning mindset, managerial support	Encourages managers to consider analytical evidence in decisions	Decisions remain intuition dominated or politically filtered
Governance and process routines	Data standards, accountability structures, privacy controls, decision routines	Stabilizes the use of analytics across business processes	Analytics use becomes inconsistent, isolated, or non-scalable
Strategic alignment	Connection between analytics projects and	Ensures that analytics addresses	Analytics investments drift toward technical

	business objectives	value-relevant problems	experimentation without business impact
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Managerial Interpretation and Decision-Making

Managerial interpretation refers to the process through which managers notice analytical signals, assign meaning to them, evaluate their relevance, and decide whether they should guide action. Research on analytics-enabled decision-making shows that data does not remove the need for judgment; instead, it changes the informational environment in which judgment occurs [14]. Managers must therefore translate analytical outputs into context-sensitive decisions that consider uncertainty, organizational constraints, and strategic priorities.

The distinction between data-driven and data-informed decision-making is central to this argument. Data-driven decision-making implies strong reliance on analytical outputs, while data-informed decision-making recognizes that managers combine analytics with experience, domain knowledge, and contextual judgment [15]. This distinction is especially important in dynamic environments, where analytical models may reveal patterns but cannot fully determine the strategic meaning of those patterns.

Managerial interpretation is also shaped by cognitive and organizational constraints. Analytical outputs can be ignored, over-trusted, misread, or politically reframed when managers lack data literacy, when organizations reward intuition over evidence, or when analytical results conflict with established routines [16]. For this reason, the conversion model treats interpretation not as a passive reading of data but as an active sensemaking process that determines whether analytics becomes usable knowledge.

Table 2 summarises the cognitive and organizational factors that shape managerial interpretation of data. These factors explain why the same analytical output may lead to different decisions across firms, units, or managerial teams, even when similar analytics capabilities are present [17, 18]. By positioning interpretation as the mediating mechanism, the model highlights that analytics creates value only when managers can evaluate evidence, integrate it with business context, and mobilize action.

Table 2. Managerial Interpretation Factors in Data-Driven Decision-Making: Cognitive Biases, Sensemaking, and Judgment Processes

Interpretation factor	Meaning in analytics-based decisions	Effect on conversion from data to action	Managerial impact
Data literacy	Ability to understand analytical methods, outputs, limits, and assumptions	Improves the credibility and usability of analytical insights	Decision makers are trained to focus on interpretation, not just data
Cognitive bias awareness	Recognition of confirmation bias, anchoring, overconfidence, and selective attention	Reduces distorted readings of data and model outputs	Communication channels are prepared for interpretation
Sensemaking capacity	Ability to connect analytical patterns with market, operational, and strategic context	Converts numerical outputs into meaningful business explanations	Useful for interpretation and action
Judgment calibration	Ability to balance analytical evidence with experience and contextual knowledge	Prevents both blind automation and unsupported intuition	Encourages data-driven but not purely data-driven decisions
Organizational trust in analytics	Degree to which managers believe analytics is reliable, relevant, and legitimate	Increases willingness to act on analytical recommendations	Improves transparency and explanation
Decision accountability	Clarity over who interprets	Links interpretation to	Accountability

	data, who decides, and who acts	implementation and outcome responsibility	and business decisions
Strategic framing	Connection between analytical findings and business priorities	Ensures that insights are interpreted in relation to value creation	Results are produced, stated, and communicated

Figure 1 explains how managerial interpretation converts analytical outputs into decision meaning and organizational action.

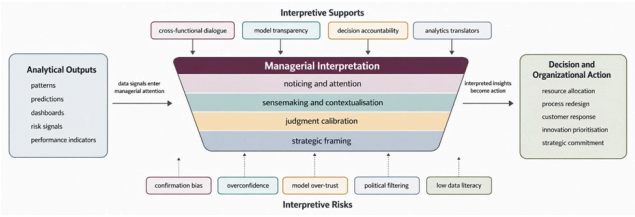


Figure 1. Managerial Interpretation as the Mediating Mechanism between Analytical Outputs and Organizational Action

Business Value Creation Mechanisms

Business value is created when interpreted analytics insights are embedded into organizational processes that improve efficiency, responsiveness, innovation, or market relevance. Studies of big data analytics capabilities show that analytics contributes to innovation when firms use analytical insight to reconfigure dynamic capabilities and respond to environmental change [19]. This means that business value is not produced by analytical outputs alone, but by the organizational mechanisms through which those outputs reshape action.

One major value mechanism is operational efficiency, where analytics supports process redesign, resource allocation, forecasting, and performance monitoring. Research on business analytics and firm performance shows that business process performance can mediate the relationship between analytics capability and firm outcomes, suggesting that value emerges through improved process execution rather than through capability possession alone [11]. In this conversion logic, managerial interpretation identifies which analytical signals are

operationally meaningful and which require redesign, escalation, or experimentation.

A second value mechanism is innovation, where analytics helps firms identify unmet needs, detect market patterns, refine offerings, and generate new service or product opportunities. Evidence on big data and innovation performance indicates that data volume and analytical sophistication do not automatically improve innovation; instead, firms must interpret data in ways that support relevant, timely, and strategically aligned innovation decisions [20]. Customer value can also be enhanced when analytics is used for personalization, segmentation, service improvement, and experience design, provided that managers connect data patterns to customer-facing action [21].

Table 3 categorises the business value creation mechanisms enabled by data and analytics. These mechanisms show how interpreted analytics insights are converted into organizational outcomes through process redesign, innovation routines, customer engagement, and business model adaptation [22]. The table therefore clarifies that value creation is a mediated organizational process rather than a direct technological effect.

Table 3. Business Value Creation Mechanisms from Data and Analytics: Efficiency, Innovation, and Customer-Centric Outcomes

Value creation mechanism	Analytical contribution	Organizational conversion process	Business value outcome
Operational efficiency	Identifies bottlenecks, waste, delays, and performance variation	Process redesign, automation support, resource reallocation, performance monitoring	Lower costs, faster execution, improved reliability
Decision quality	Provides evidence, forecasts, scenario analysis, and risk signals	Managerial interpretation, deliberation routines, accountability mechanisms	Better strategy and operational decisions

Product and service innovation	Detects unmet needs, usage patterns, and emerging opportunities	Experimentation, offering redesign, innovation portfolio adjustment	New improved offerings
Customer experience enhancement	Supports segmentation, personalization, churn prediction, and service recovery	Customer journey redesign, targeted engagement, service adaptation	High satisfaction, loyalty retention
Revenue growth	Reveals pricing opportunities, demand patterns, and cross-selling potential	Commercial strategy adjustment, sales prioritization, market targeting	Increased sales, monetization potential
Business model renewal	Identifies new data-enabled services, platforms, or ecosystem opportunities	Strategic reframing, partnership formation, monetization design	New revenue logic, scaled value propositions
Risk reduction	Detects anomalies, vulnerabilities, and uncertainty patterns	Monitoring systems, compliance routines, mitigation decisions	Lower exposure, operational and strategic resilience

Competitive Advantage through Data Use

Competitive advantage emerges when business value created through analytics becomes difficult for competitors to replicate. The resource-based logic of data use suggests that data and analytics may support advantage when they are valuable, context-specific, embedded in routines, and combined with complementary capabilities [23]. However, data itself is rarely sufficient for sustained advantage because competitors may acquire similar technologies, hire similar analysts, or access comparable external data sources.

The conversion from value to advantage therefore depends on complementarity. Analytics-generated value becomes more defensible when data assets are combined with organizational knowledge, managerial judgment, proprietary processes, customer relationships, and learning routines [17]. Research on dynamic and operational capabilities shows that competitive performance improves when analytics capability strengthens broader organizational capabilities rather than remaining isolated in technical units [17].

Data monetization illustrates this advantage logic because firms can extract strategic value from data only when they design viable pathways for internal optimization, external data products, or data-enabled services. Work on data monetization shows that firms must configure data assets, governance structures, business models, and customer value propositions to convert data into economic value [24, 25]. This reinforces the argument that advantage depends on organizational interpretation and strategic design, not simply on owning data.

Table 4 illustrates how data-driven insights are converted into competitive advantage. The pathways emphasize that analytics-based advantage is strongest when insights are tied to resource attributes, organizational complementarities, and isolating mechanisms that competitors cannot easily copy [26]. The table therefore connects business value creation to strategic defensibility.

Table 4. Pathways from Data Use to Competitive Advantage: Resource Attributes, Complementarities, and Isolating Mechanisms

Competitive pathway	Strategic logic	Conversion requirement	Advantage condition
Valuable data use	Data improves decisions, processes, offerings, or customer relationships	Managers identify which data signals are linked to strategic value	Data use improves outcomes that matter for competitive advantage
Rare insight generation	Firm develops insights competitors do not possess or	Proprietary data sources and contextual interpretation	Insights reveal market, customer, or operational opportunities

	cannot easily infer	are combined	opportunities arise earlier
Imperfect imitability	Competitors cannot easily reproduce the firm's data routines or learning history	Analytics is embedded in tacit routines, domain knowledge, and culture	Advantage is protected by causal ambiguity and organizational complexity
Complementary capability	Data is combined with dynamic capabilities, operational routines, and managerial expertise	Analytics teams, managers, and business units coordinate interpretation and action	Value becomes organization-wide rather than tool-specific
Data network effects	More use generates richer data, better models, and improved customer or process knowledge	Feedback loops are designed into operations and customer interactions	Learning accumulates faster than competitors can imitate
Data monetization	Data supports new services, revenue models, or ecosystem positions	Data governance, market framing, and value proposition design are aligned	Data becomes a source of revenue and strategic positioning
Competitive resilience	Analytics improves adaptation under uncertainty and competitive pressure	Managers use analytics to anticipate change and reallocate resources	Advantage persists through fast sensing and response

Proposed Data-to-Business-Value Conversion Model

The Data-to-Business-Value Conversion Model proposes a causal chain in which analytics capability provides the potential for insight, managerial interpretation converts insight into decision meaning, business value creation mechanisms translate decisions into outcomes, and competitive advantage emerges when those outcomes become strategically defensible. This logic integrates research showing that analytics capability affects performance through dynamic capabilities, operational capabilities, and value creation mechanisms [1, 27]. The model therefore moves beyond a simple capability-performance relationship by specifying the interpretive and organizational stages that connect data to advantage.

The first relationship in the model links analytics capability to managerial interpretation. Analytics capability improves the quality, availability, and analytical richness of information, but managers must still evaluate the relevance, reliability, and strategic meaning of analytical outputs [14]. This relationship is moderated by data culture and organizational readiness, because managers are more likely to interpret and use analytics when evidence-based reasoning is institutionally supported [28].

The second relationship links managerial interpretation to business value creation. When managers interpret analytical outputs effectively, they can prioritize process redesign, customer experience improvement, innovation initiatives, and business model renewal [21]. Yet this relationship is conditioned by organizational inertia, because even well-interpreted insights may fail to generate value if routines, incentives, or structures prevent implementation [29].

Table 5 presents the complete Data-to-Business-Value Conversion Model. The model incorporates analytics capability, managerial interpretation, business value mechanisms, competitive advantage pathways, and key moderating conditions derived from analytics capability and strategic information systems research [30]. It provides a conceptual basis for future empirical testing of how firms convert data potential into realized business outcomes.

Table 5. Data-to-Business-Value Conversion Model: Constructs, Relationships, and Transformation Logic

Model element	Conceptual definition	Main relationship in the model	Transformation logic
Data and analytics capability	Firm capacity to collect, manage, analyze, and deploy data	Foundational antecedent	Creates analytical potential for decision relevance
Managerial interpretation	Managerial process of assigning meaning, relevance, and actionability to analytical outputs	Central mediating mechanism	Converts analytical outputs into strategic operational decisions
Business value creation mechanisms	Organizational pathways through which decisions improve efficiency, innovation, customer value, revenue, or risk control	Proximal outcome stage	Transforms interpretive insights into measurable organizational benefits
Competitive advantage	Strategic position created when analytics-enabled value is valuable, difficult to imitate, and embedded in complementary capabilities	Distal strategic outcome	Converts realized business value into differentiated performance
Data culture	Shared expectation that decisions should engage with evidence and analytical reasoning	Moderator between capability and interpretation	Strengthens managerial willingness to use questionable analytics

Environmental dynamism	Degree of market, technological, and competitive change	Moderator across the conversion chain	Increase value of interpretation and action
Leadership support	Senior management commitment to analytics, learning, and value realization	Moderator of implementation and scaling	Aligns a project strategy priorities resource commitment
Organizational inertia	Resistance created by routines, incentives, structures, or legacy assumptions	Negative moderator between interpretation and value creation	Weaken conversion insight action
Feedback learning	Continuous evaluation of whether analytics-based decisions produced intended outcomes	Reinforcing mechanism	Improve data conversion interpretation routine strategy decision

Figure 2 presents the complete Data-to-Business-Value Conversion Model linking analytics capability, managerial interpretation, business value creation, and competitive advantage.

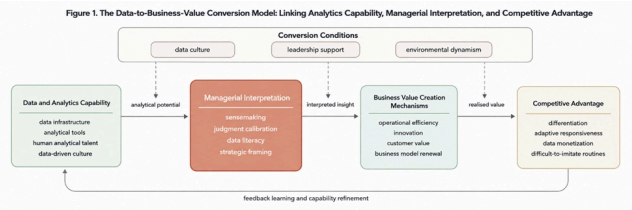


Figure 2. The Data-to-Business-Value Conversion Model: From Analytics Capability to Competitive Advantage through Managerial Interpretation

Application Scenarios

In a retail scenario, the model explains why customer analytics does not automatically improve performance. A retailer may possess transaction data, loyalty records, and predictive models, but value depends on whether managers interpret customer signals as pricing opportunities, personalization needs, assortment changes, or service redesign priorities [9]. If interpretation is weak, the firm may produce dashboards without changing customer-facing decisions.

In a manufacturing scenario, predictive maintenance analytics can create value by reducing downtime, improving asset utilization, and supporting operational planning. However, the conversion chain requires managers to trust predictive signals, redesign maintenance routines, coordinate production schedules, and evaluate trade-offs between preventive action and operational disruption [13]. Analytics capability becomes valuable only when interpreted insights are embedded into operational decision routines.

In a digital platform or service firm, data may support new revenue models, ecosystem positioning, and data-enabled services. The model suggests that monetization requires more than technical analytics, because managers must interpret which data assets are commercially meaningful, ethically usable, and strategically differentiating [24]. Breakdown occurs when firms identify analytical opportunities but fail to design a viable value proposition or governance model.

Research and Practice Implications

For research, the Data-to-Business-Value Conversion Model provides a basis for testing mediated and moderated relationships rather than treating analytics capability as a direct predictor of performance. Future studies can examine whether managerial interpretation mediates the relationship between analytics capability and business value, and whether data culture, leadership support, competitive intensity, or organizational inertia strengthen or weaken this relationship [26, 28]. Process-oriented studies are especially important because conversion unfolds through sequential decisions rather than through a single capability-performance link.

The model also has implications for measurement development. Researchers should distinguish analytics

capability from interpretation quality, value creation mechanisms, and competitive outcomes, because combining these constructs risks obscuring the actual conversion process [7]. Measures of interpretation may include data literacy, judgment calibration, sensemaking routines, cross-functional dialogue, and the extent to which managers translate analytical outputs into accountable decisions.

For practice, the model suggests that firms should not evaluate analytics maturity only by the scale of data infrastructure, tool sophistication, or technical talent. Managers should also invest in interpretation routines, decision forums, analytics translators, and feedback systems that show whether analytics-based decisions produce intended value [12]. The practical challenge is to manage the whole conversion chain from data inputs to strategic outcomes, rather than assuming that better analytics automatically produces better performance.

Figure 3 shows the main breakdown points and managerial interventions across the data-to-business-value conversion chain.

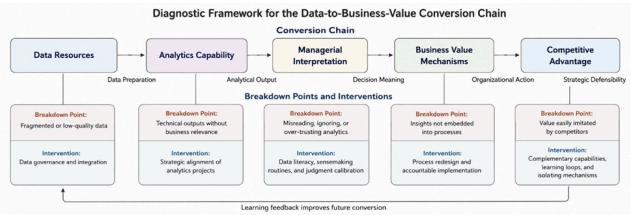


Figure 3. Conversion Breakdowns and Managerial Interventions in the Data-to-Business-Value Chain

Conclusion

This article developed the Data-to-Business-Value Conversion Model to explain how firms convert data and analytics capability into business value and competitive advantage. The model argues that analytics capability creates potential, but potential becomes valuable only when managers interpret analytical outputs and connect them to organizational action. It therefore reframes the

data-to-value problem as a conversion problem rather than a purely technical capability problem.

The article's central contribution is the positioning of managerial interpretation as the missing link between analytics capability and realized business value. By identifying interpretation as a mediating mechanism, the model clarifies why firms with similar data resources and analytical tools may achieve very different outcomes. It also shows that competitive advantage depends on whether analytics-enabled value is embedded in complementary capabilities, routines, and isolating mechanisms.

Future research should empirically validate the model, refine its constructs, and examine how the conversion chain operates across industries, organizational sizes, and competitive environments. Managers should focus not only on acquiring data and analytics capability, but also on building the interpretive and organizational conditions required to act on analytical insight. The strategic value of data lies not in possession, but in conversion.

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