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From Information Advantage to Predictive Advantage: The Strategic Significance of Advanced Analytics in Contemporary Organizations

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Abstract

In today's hyper-competitive digital environment, organizations are shifting from traditional information advantage—rooted in descriptive data analysis—to predictive advantage, where advanced analytics enable foresight and proactive strategy. This conceptual article synthesizes insights from the existing literature to examine how advanced analytics, big data, and machine learning transform organizational capabilities and strategic decision-making. The transition involves progressing through descriptive, diagnostic, predictive, and prescriptive analytics stages, ultimately embedding predictive intelligence into core business processes. A novel conceptual framework, the Strategic Predictive Advantage Framework (SPAF), is introduced as a multi-layered architecture comprising data acquisition and integration, analytics processing and modeling, predictive insight generation, strategic decision integration, organizational learning and feedback, and capability development. SPAF delineates bidirectional flows and feedback loops that convert raw information into actionable predictive superiority, fostering sustained competitive advantage. By integrating literature on data-driven strategy, analytics capabilities, and organizational transformation, the paper demonstrates how predictive modeling reconfigures decision systems, enhances forecasting accuracy, and creates dynamic learning cycles within organizations. Theoretical contributions advance digital business and management studies by reframing competitive advantage as predictive rather than informational. Practical implications urge leaders to invest in analytics infrastructure, cultural alignment, and iterative feedback mechanisms to navigate volatility. The framework offers a roadmap for realizing predictive intelligence as a core strategic asset in contemporary organizations.

Keywords Competitive advantage, Organizational capabilities, Strategic management, Big data analytics, Advanced analytics, Predictive advantage

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Introduction

The contemporary organizational landscape is defined by unprecedented data volumes and computational power, compelling firms to evolve beyond static information advantages toward dynamic predictive capabilities. Historically, competitive edges stemmed from superior access to market intelligence and historical records [1],

enabling reactive decision-making. However, the explosive growth of big data and advanced analytics has redefined strategic advantage [2], positioning predictive foresight as the new source of differentiation [3–6]. Organizations now leverage machine learning algorithms and predictive modeling to anticipate market shifts, customer behaviors, and operational disruptions before they materialize [3], thereby converting uncertainty into opportunity [7].

This transition is not merely technological but fundamentally strategic. Advanced analytics encompass a maturity continuum: descriptive analytics summarize past events, diagnostic analytics explain why they occurred, predictive analytics forecast future scenarios [4], and prescriptive analytics recommend optimal actions [8]. Firms that master this progression achieve what this paper terms “predictive advantage”—a capability that integrates analytics into organizational DNA [5], enabling proactive strategy formulation and execution [9, 10]. Empirical evidence from recent scholarship indicates that organizations that invest in big data analytics capabilities report enhanced firm performance, innovation, and resilience [1, 7, 11, 12]. For instance, dynamic capabilities theory illustrates how analytics transform resources into sustained advantages by reconfiguring processes in response to environmental turbulence [9, 13, 14].

The strategic significance of this shift is amplified in volatile markets characterized by rapid technological change, geopolitical uncertainty, and evolving consumer expectations. Predictive systems allow executives to simulate multiple futures [6], optimize resource allocation [15–20], and mitigate risks with unprecedented precision [21]. Machine learning applications further democratize decision-making by embedding intelligence across functions—from supply chain optimization to customer relationship management—creating organization-wide predictive intelligence [11, 17, 22–24]. Yet, realizing this potential demands more than technology adoption; it requires cultural transformation [15], leadership commitment [18], and the development of analytics-driven governance structures [25, 26].

The literature in premier journals such as *Strategic Management Journal*, *MIS Quarterly*, and *Journal of Business Research* consistently highlights that firms that fail to advance from information to predictive paradigms risk obsolescence [2, 6, 22]. Conversely, leaders in analytics maturity report superior competitive positioning through improved forecasting accuracy [7] and agile responses [10, 27]. This article addresses a critical gap: while prior work has examined isolated aspects of big data value creation or predictive modeling in silos, few conceptual frameworks holistically map the transition to predictive advantage as a systemic, feedback-rich architecture [5, 9, 28]. Moreover, existing studies often treat analytics capabilities as static assets rather than dynamic, learning-oriented systems that evolve through continuous interaction between predictive outputs and strategic outcomes [8, 13, 18]. This oversight

limits both theoretical understanding and practical application, as organizations lack integrative guidance for building self-reinforcing predictive capabilities.

By synthesizing insights from peer-reviewed publications spanning management information systems, strategic management, and organizational behavior, this paper develops an original conceptual framework—the strategic predictive advantage framework (SPAF)—to guide organizations in architecting predictive intelligence. SPAF emphasizes multi-layer integration, directional data flows, and closed-loop learning [10], illustrating how predictive advantage emerges from the interplay of technological, human, and organizational elements [11, 29]. The framework’s novelty lies in its explicit focus on feedback loops that evolve models in real time [8], ensuring predictions inform actions that, in turn, refine future forecasts [14, 20]. This cyclical architecture distinguishes SPAF from prior models that conceptualize analytics as a linear process from data collection to decision-making [4], thereby failing to capture the iterative refinement essential for sustained advantage [9, 16].

Theoretically, the paper extends resource-based view and dynamic capabilities perspectives by positioning predictive analytics as a higher-order capability that transcends traditional information processing [1, 6, 13]. Whereas the resource-based view emphasizes heterogeneous resource endowments, predictive advantage stems from the capacity to learn from data and adapt predictive models more quickly than competitors [5]. This capability becomes increasingly difficult to imitate as feedback loops deepen [12, 19]. Practically, it offers executives a blueprint for embedding analytics into strategic processes [12], fostering cultures of foresight [15], and measuring returns on predictive investments [21]. In an era where foresight equates to survival, understanding this transition is imperative for scholars and practitioners alike. Subsequent sections synthesize foundational literature, articulate SPAF in detail, and illuminate pathways for organizational implementation [4], ultimately demonstrating that predictive advantage is not an aspirational ideal but an achievable strategic imperative [7, 22, 28].

Literature Synthesis and Conceptual Foundations

The scholarly discourse from 2017 to 2023 reveals a definitive evolution in how organizations harness analytics

for competitive gain, marking a paradigmatic shift from information-centric to prediction-centric paradigms. Early contributions established big data analytics capabilities (BDAC) as foundational to performance improvements [1]. Yet, subsequent work has progressively refined our understanding of the mechanisms, contingencies, and architectures through which predictive intelligence creates sustainable advantage [2, 3]. This synthesis organizes the literature into five interconnected streams: (1) the capability-based view of analytics value creation, (2) the analytics maturity continuum, (3) machine learning and predictive modeling as decision enablers, (4) organizational and governance mechanisms, and (5) emerging critiques and conceptual gaps.

The capability-based view of analytics value creation

A foundational thread in the literature positions big data analytics capabilities within the theoretical lenses of the resource-based view (RBV) and dynamic capabilities theory. One seminal study provided evidence that dynamic capabilities—specifically sensing, seizing, and transforming—mediate the relationship between big data analytics investments and firm performance outcomes [1]. This mediation suggests that analytics assets alone do not generate advantage; rather, it is the organizational capacity to continuously reconfigure resources in response to analytics-derived insights that yields sustained differentiation. Extending this logic, subsequent research within supply chain contexts demonstrated that predictive analytics enhance not only operational efficiency but also collaborative performance and systemic resilience [2], particularly when embedded within inter-organizational information architectures [8, 24].

The mediating role of organizational factors in translating analytics investments into tangible value emerges as a recurrent theme across high-impact journals. One study assessing business value creation in European firms concluded that analytics maturity directly influences decision quality, but only when strategically aligned with organizational objectives and decision-making structures [3]. This alignment imperative was further developed in a multi-level research framework for creating strategic business value from big data [6], emphasizing the dynamic interplay between technological infrastructure, process redesign, and human capital development. Subsequent work identified big data analytics capabilities as indirect

drivers of competitive performance [5], operating through the enhancement of both dynamic capabilities—such as absorptive capacity and strategic flexibility—and operational capabilities, including process efficiency and responsiveness [10]. These studies collectively reframe analytics not as a standalone resource but as a capability amplifier that multiplies the value of existing organizational competencies.

In emerging economy contexts, an examination of governance mechanisms that enable analytics-driven decision-making revealed that formalized data governance structures, coupled with distributed decision-making authority, create conditions in which predictive insights translate into strategic agility [9]. These findings complicate simplistic narratives of technological determinism, underscoring that cultural and structural factors mediate the analytics-value link in ways that vary across institutional environments.

The analytics maturity continuum: from description to prescription

A second conceptual pillar concerns the staged progression through which organizations advance along the analytics maturity curve. The literature consistently traces a trajectory from descriptive analytics—which summarize historical patterns—through diagnostic analytics that explain causality, predictive analytics that forecast future states [4], and finally prescriptive analytics that recommend optimal courses of action [20, 23]. Within this continuum, predictive analytics occupies a pivotal position as the bridge between retrospective understanding and prospective action, serving as the gateway to strategic foresight.

One study illustrated this progression within healthcare contexts, demonstrating how predictive modeling improves both operational efficiency and patient outcomes when layered upon robust descriptive and diagnostic foundations [4]. This work highlights a crucial insight: predictive capabilities do not substitute for foundational analytics but rather depend upon them, as the accuracy and reliability of forecasts are contingent upon the quality and comprehensiveness of historical data and causal understanding. Another study advanced a nuanced framework for advanced analytics in managerial decision support [22], emphasizing that diagnosticity—the capacity to explain why patterns occur—functions as a prerequisite for predictive reliability. Without causal insight, predictive

models risk capturing spurious correlations that fail under changing conditions, a limitation that underscores the importance of theoretical grounding in analytics implementation.

Additional research extended these insights to supply chain contexts, demonstrating how predictive tools optimize upstream and downstream coordination by enabling anticipatory inventory management, demand forecasting, and risk mitigation [23]. This work illustrates that predictive advantage in operational domains accrues not merely from model sophistication but also from integrating predictive outputs into routine decision workflows, creating closed loops in which forecasts inform actions that, in turn, generate new data to refine future predictions.

Machine learning and predictive modeling as transformative enablers

The third stream centers on machine learning (ML) and predictive modeling as transformative enablers of organizational decision-making. One study demonstrated that big data analytics capabilities foster business model innovation through the mediating mechanism of entrepreneurial orientation [11], suggesting that predictive intelligence expands firms' strategic imagination by revealing previously unrecognized opportunities and threat trajectories. This finding aligns with the broader literature on digital transformation, which posits that analytics capabilities reconfigure not only operational processes but also the fundamental logic of value creation and capture.

Compelling evidence of this transformative potential during periods of environmental turbulence emerged from research examining how analytics capabilities sustained competitive advantage in service firms throughout the COVID-19 crisis [12]. This research reveals that organizations with mature predictive capabilities demonstrated superior resilience, as they could simulate multiple scenario trajectories, anticipate demand fluctuations, and dynamically reallocate resources in response to unfolding disruptions. This crisis context served as a natural experiment, underscoring that predictive advantage is most valuable precisely when uncertainty is highest and traditional planning mechanisms fail.

These findings were extended to strategy and hospitality contexts, respectively [13, 14], emphasizing firm-specific knowledge and knowledge-based dynamic capabilities as

amplifiers of predictive outcomes. In these studies, the capacity to integrate predictive model outputs with tacit organizational knowledge—what might be termed “analytics-informed intuition”—emerged as a distinctive capability that differentiates high-performing firms from those that merely adopt analytics tools without embedding them into organizational cognition.

Implementation barriers, enablers, and governance

Conceptual foundations also address the organizational conditions under which predictive capabilities flourish or flounder. A multidimensional conceptualization of big data analytics capability identified technical infrastructure, managerial processes, and cultural orientations as co-constitutive dimensions that collectively determine analytics effectiveness [15]. This framework challenges technocentric views of analytics adoption, asserting that investments in algorithms and infrastructure yield diminishing returns absent corresponding investments in organizational culture and managerial cognition.

Subsequent work demonstrated mediation through business process innovation and strategy alignment [16], showing that analytics capabilities create value indirectly by enabling process redesign and strategic repositioning [17]. These findings suggest that predictive advantage is less about having superior forecasts than about having the organizational capacity to act on them faster and more effectively than competitors. This capacity requires both structural flexibility and cultural receptivity to data-driven insights.

Broader reviews critiqued persistent implementation challenges [19] while advocating diagnosticity and data quality as critical predictors of decision-making efficacy [20]. These reviews reveal that many organizations struggle not with model development but with data integration, legacy system compatibility, and the cultivation of analytical talent—challenges that require sustained organizational commitment rather than one-time investments. Additional research identified factors influencing the quality of big data decision-making [21], reinforcing the need for integrated systems that seamlessly connect data acquisition, processing, visualization, and action initiation. This work highlights that predictive advantage depends on eliminating organizational silos that fragment data and decision authority, with profound implications for organizational design.

Emerging critiques and conceptual gaps

Despite the richness of this literature, several conceptual gaps warrant attention. First, existing studies predominantly treat analytics capabilities as static endowments rather than dynamic, learning-oriented systems that evolve through iterative feedback between predictive outputs and strategic outcomes [5, 8, 13]. This static conceptualization limits our understanding of how organizations develop predictive capabilities over time, particularly how they learn from prediction errors and refine models through experience. Second, while the analytics maturity continuum is widely referenced, few studies specify the mechanisms that enable progression from one stage to the next, leaving organizations without clear guidance on how to advance their capabilities. Third, the literature exhibits a fragmented treatment of feedback loops. Although individual studies acknowledge the importance of learning and iteration, integrative frameworks that explicitly model bidirectional flows between prediction and action remain underdeveloped [4, 9, 14].

These gaps are particularly consequential because predictive advantage, unlike traditional information advantage, is inherently recursive. Predictions shape actions; actions generate new data; new data refine predictions. Organizations that fail to close this loop—that treat prediction as a one-way output rather than a recursive process—inevitably see their predictive models degrade over time as environmental conditions shift. Conversely, organizations that architect closed-loop learning systems can continuously adapt, creating self-reinforcing cycles of predictive refinement that competitors cannot easily replicate.

Toward an Integrative Framework

Synthesizing across these five streams, several integrative principles emerge. First, predictive advantage requires the simultaneous development of technological, human, and organizational capabilities—a multidimensional configuration that resists simplistic prescriptions. Second, the transition to predictive paradigms entails not merely tool adoption but fundamental organizational transformation, affecting decision-making structures, governance mechanisms, and cultural norms. Third, feedback loops are central to sustained advantage, as they transform

predictive analytics from a static capability into a learning system that improves with use. Fourth, context matters: the mechanisms through which predictive analytics create value vary across industries, institutional environments, and organizational characteristics, suggesting that frameworks must accommodate contingency rather than offer universal prescriptions.

The literature thus provides a robust foundation for an integrative framework that explicitly theorizes predictive advantage as a systemic, feedback-rich architecture. Such a framework must address the gaps identified above by conceptualizing analytics maturity as a dynamic process, specifying the mechanisms that enable progression, and modeling the recursive relationships that sustain predictive superiority over time. The SPAF, introduced in the following section, responds to these theoretical and practical imperatives.

Later works expand to cultural and ambidextrous dimensions. Rialti *et al.* [28] reviewed ambidextrous organizations leveraging big data for innovation, while Pappas *et al.* and Fosso Wamba *et al.* outlined research agendas for realizing business value through longitudinal evidence [25, 27]. Ji-fan Ren *et al.* [26] and Zhang *et al.* [29] modeled quality dynamics and supply chain roles, confirming the impact of predictive analytics on performance. Collectively, these 29 studies establish that predictive advantage arises when analytics transcend information processing to embed foresight into strategic routines, supported by feedback mechanisms that continuously refine models [7, 8, 10, 14, 20]. This synthesis reveals a gap: while individual capabilities and outcomes are well-documented, no unified architecture yet maps the systemic transition from information to predictive advantage. The following section addresses this gap through the SPAF.

The strategic predictive advantage architecture: Introducing the SPAF model

To operationalize the transition from information advantage to predictive advantage, this paper introduces the SPAF—a novel multi-layered conceptual architecture designed for contemporary organizations. SPAF comprises six interdependent components that collectively transform raw data into predictive intelligence and strategic action: (1) data acquisition and integration, (2) analytics processing

and modeling, (3) predictive insight generation, (4) strategic decision integration, (5) organizational learning and feedback, and (6) capability development.

The architecture is structured as a hierarchical yet cyclical system. Data acquisition and integration form the foundational layer, aggregating structured, unstructured, and real-time sources into unified repositories [1, 19, 29]. This layer feeds upward into analytics processing and modeling, where machine learning algorithms and statistical techniques extract patterns and build diagnostic models [5, 22, 23]. Predictive insight generation then employs advanced forecasting techniques to simulate future states, moving beyond historical description to probabilistic foresight [4, 10, 20]. Outputs flow to strategic decision integration, embedding predictions directly into executive processes, resource allocation, and business model reconfiguration [6, 11, 15].

Bidirectional feedback loops are central to SPAF's distinctiveness. Outcomes from strategic actions return to lower layers, refining data quality, algorithms, and models in real time [8, 14, 26]. A transversal organizational learning and feedback component connects all layers, institutionalizing lessons and fostering a culture of continuous adaptation [7, 9, 27]. Finally, capability development operates as an overarching mechanism, building human, technological, and cultural competencies that sustain the entire architecture [12, 13, 28]. **Figure 1** illustrates a vertical, layered diagram with five ascending rectangles connected by solid upward arrows labeled Data & Model Flow.



Figure 1. Conceptual architecture of predictive advantage.

Table 1 specifies the mechanism of predictive advantage within SPAF by showing how each layer produces strategic value, what feedback signal enables refinement, and what capability breakdown threatens recursive advantage.

Table 1. Mechanisms of predictive advantage in spaf: layer functions, strategic outputs, feedback signals, and capability risks

SPAF component	Primary function	Immediate strategic output	Feedback signal sustains learning
Data acquisition and integration	Consolidates structured, unstructured, and real-time inputs into a decision-ready data infrastructure	Shared organizational visibility and reliable signal capture	Data completeness, latency, interoperability, and quality variance
Analytics processing and modeling	Translates raw data into patterns, features, causal structures, and trainable models	Analytical representations of drivers, anomalies, and probable relationships	Model accuracy, feature instability, recalibration needs
Predictive insight generation	Converts models into forecasts, scenarios, risk probabilities, and forward-looking signals	Actionable foresight under uncertainty	Forecast calibration, scenario divergence, and signal usefulness
Strategic decision integration	Embeds predictions into resource allocation, process redesign, timing, and strategic choice	Faster, anticipatory, and coordinated strategic action	Decision uptake, speed of execution, variance, business impact

Organizational learning and feedback	Captures the consequences of actions and feeds outcomes back into data, models, and routines	Institutionalized improvement and adaptive refinement	Outcomes vary; predict action g learning speed, policy re
Capability development	Builds human, technological, and cultural capacity to sustain the whole architecture	Enduring predictive competence and scalability	Skill gro adopte dept govern maturity infrastru readin

SPAF's strength lies in its explicit representation of prediction-to-action dynamics and closed-loop learning, distinguishing it from prior linear maturity models [3, 16, 25]. Organizations adopting SPAF can systematically evolve analytics capabilities, ensuring predictive advantage becomes embedded and self-reinforcing [17, 21, 24]. This architecture thus provides both theoretical coherence and practical guidance for digital transformation.

Predictive analytics transformation: evolving organizational capabilities

The transition from information advantage to predictive advantage is fundamentally a capability evolution that reorients organizations along the analytics maturity continuum. Descriptive analytics once sufficed for retrospective reporting, yet contemporary scholarship demonstrates that firms must deliberately progress through diagnostic, predictive, and prescriptive stages to achieve strategic superiority [4, 20, 23]. This progression is not linear but iterative, with each stage building layered competencies that amplify foresight and responsiveness.

The maturity continuum of analytics in strategic management

Organizations begin by consolidating historical data into descriptive dashboards that illuminate what has occurred, yet this static view yields diminishing returns in turbulent environments [1, 3, 19]. Diagnostic analytics then interrogates causality—why events unfolded—through

correlation mining and root-cause algorithms, laying the groundwork for predictive modeling [21, 22]. Predictive analytics elevates the capability set by deploying machine learning ensembles, time-series forecasting, and neural networks to generate probabilistic future scenarios with quantified confidence intervals [10, 26, 29]. Finally, prescriptive analytics closes the loop by recommending optimal actions, integrating optimization solvers and simulation engines that translate predictions into executable strategies [8, 23, 24].

Empirical evidence from the synthesized literature confirms that firms mastering this continuum achieve measurable gains in performance and resilience [7, 12, 14]. The SPAF framework operationalizes this maturity path by embedding each stage within its six layers, ensuring that capability development is not an afterthought but a transversal mechanism that continuously upgrades human and technological resources [13, 15, 28].

Machine learning as catalyst for predictive modeling

Machine learning applications serve as the catalytic engine within SPAF's analytics processing layer, converting raw inputs into high-fidelity predictive outputs [5, 11, 17]. Supervised algorithms learn from labeled historical patterns to forecast demand, churn, or risk; unsupervised techniques uncover latent structures in unstructured data streams; reinforcement learning refines decision policies through simulated trial-and-error [2, 6, 25]. These techniques do not operate in isolation; SPAF's feedback loops feed actual outcomes back into training datasets, enabling continuous model retraining and drift detection [8, 14, 20]. Consequently, predictive models evolve from static artifacts into living intelligence systems that adapt in real time, a hallmark of predictive advantage [10, 27].

Analytics-Enabled Strategic Decision Making: Embedding Foresight in Operations

Predictive advantage materializes only when foresight permeates every organizational process and decision node. SPAF's strategic decision integration layer ensures that predictive insights are not siloed reports but embedded decision triggers that reconfigure resource allocation,

supply chains, and customer engagements instantaneously [6, 11, 16].

Data-driven competitive advantage in volatile markets

In hyper-volatile markets, predictive intelligence converts uncertainty into optionality. Organizations equipped with SPAF can simulate macroeconomic shocks, competitor moves, or regulatory shifts, thereby optimizing inventory, pricing, and market entry strategies before events unfold [9, 12, 24]. This proactive posture contrasts sharply with reactive, information-based strategies, delivering first-mover advantages and risk mitigation that translate into sustained market-share gains [13, 14, 29]. The literature consistently positions such capability as a higher-order dynamic competence that rivals cannot easily imitate once institutionalized [1, 7, 10].

Integration of predictive insights into organizational processes

SPAF's architecture mandates horizontal integration across functions. Marketing teams receive propensity-to-buy scores that trigger personalized campaigns; operations receive failure-probability forecasts to schedule preventive maintenance; and finance receives cash-flow simulations to inform capital structure decisions [4, 23, 25]. These integrations are governed by the organizational learning component, which codifies successful prediction-action pairings into updated policies and knowledge repositories [27, 28]. The result is a self-reinforcing system in which prediction accuracy improves with each cycle, deepening competitive moats [17, 21, 26].

Navigating the Path to Predictive Superiority: Implementation Pathways and Systemic Enablers

Realizing SPAF in practice demands deliberate orchestration of technological, cultural, and leadership elements. While the framework provides the architectural blueprint, successful deployment hinges on addressing entrenched barriers and cultivating enabling conditions. Legacy organizational cultures often resist the shift from intuition-driven to prediction-driven decision-making, viewing analytics outputs as threats rather than

augmentations [9, 15, 28]. Siloed data architectures further impede the data acquisition layer, creating fragmented inputs that undermine model integrity [19, 21]. SPAF counters these barriers by positioning capability development as an explicit layer that invests in cross-functional analytics literacy programs and incentive structures aligned with predictive outcomes [12–14]. Executives must champion SPAF by allocating resources to continuous model governance and by modeling data-informed risk-taking [6, 11, 22]. Leadership narratives that celebrate predictive wins—such as averted disruptions or captured opportunities—reinforce the cultural shift toward foresight [7, 16, 27]. The framework's feedback loops further empower leaders by delivering transparent metrics on prediction accuracy and business impact, enabling evidence-based refinement of strategic priorities [8, 20, 26].

Conclusion

As organizations confront accelerating change, predictive advantage is no longer optional but existential. Those that internalize SPAF will not merely survive disruption—they will preempt and shape it. Future research should empirically validate SPAF across sectors and explore its intersections with emerging technologies such as generative AI and quantum computing. Ultimately, the article affirms that the strategic significance of advanced analytics lies not in data volume but in the predictive intelligence it yields, heralding a new era of foresight-driven management in contemporary digital business.

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References

- Wamba SF, Gunasekaran A, Akter S, Ren SJF, Dubey R, Childe SJ. Big data analytics and firm performance: Effects of dynamic capabilities. *J Bus Res.* 2017;70:356-65.
- Gunasekaran A, Papadopoulos T, Dubey R, Wamba SF, Childe SJ, Hazen B, et al. Big data and predictive analytics for supply chain and organizational performance. *J Bus Res.* 2017;70:308-17.
- Côrte-Real N, Oliveira T, Ruivo P. Assessing business value of Big Data Analytics in European firms. *J Bus Res.* 2017;70:379-90.
- Wang Y, Kung LA, Byrd TA. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technol Forecast Soc Change.* 2018;126:3-13.
- Mikalef P, Pappas IO, Krogstie J, Giannakos M. Big data analytics capabilities: a systematic literature review and research agenda. *Inf Syst E-Bus Manage.* 2018;16(3):547-78.
- Grover V, Chiang RH, Liang TP, Zhang D. Creating strategic business value from big data analytics: A research framework. *J Manag Inf Syst.* 2018;35(2):388-423.
- Mikalef P, Boura M, Lekakos G, Krogstie J. Big data analytics and firm performance: Findings from a mixed-method approach. *J Bus Res.* 2019;98:261-76.
- Dubey R, Gunasekaran A, Childe SJ, Wamba SF, Roubaud D, Foropon C. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *Int J Prod Econ.* 2019;210:120-36.
- Shamim S, Zeng J, Khan Z, Zia NU. Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technol Forecast Soc Change.* 2020;161:120315.
- Mikalef P, Krogstie J, Pappas IO, Pavlou P. Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Inf Manag.* 2020;57(2):103169.
- Ciampi F, Demi S, Magrini A, Marzi G, Papa A. Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *J Bus Res.* 2021;123:1-13.
- Behl A, Gaur J, Pereira V, Yadav R, Laker B. Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19: A multi-theoretical approach. *J Bus Res.* 2022;148:378-89.
- Dahiya R, Le S, Ringov D. Big data analytics and competitive advantage: the strategic role of firm-specific knowledge. *J Strategy Manag.* 2022;15(2):175-93.
- Horng JS, Liu CH, Chou SF, Yu TY, Hu DC. Role of big data capabilities in enhancing competitive advantage and performance in the hospitality sector: Knowledge-based dynamic capabilities view. *J Hosp Tour Manag.* 2022;51:22-38.
- Gupta M, George JF. Toward the development of a big data analytics capability. *Inf Manag.* 2018;55(8):1049-65.
- Akter S, Wamba SF, Gunasekaran A, Dubey R, Childe SJ. How to improve firm performance using big data analytics capability and business strategy alignment? *Int J Prod Econ.* 2018;205:185-96.
- Raguseo E, Vitari C. The effect of big data analytics capability on firm performance: the mediating role of business process innovation. *J Bus Res.* 2018;85:483-95.

Müller O, Junglas I, Brocke JV, Debortoli S. Utilizing big data analytics for information systems research: challenges, promises and guidelines. *Eur J Inf Syst.* 2016;25:289-302.

Sivarajah U, Kamal MM, Irani Z, Weerakkody V. Critical analysis of Big Data challenges and analytical methods. *J Bus Res.* 2017;70:263-86.

Ghasemaghaei M, Calic G. Can big data improve firm decision quality? The role of data quality and data diagnosticity. *Decis Support Syst.* 2019;120:38-49.

Janssen M, van der Voort H, Wahyudi A. Factors influencing big data decision-making quality. *J Bus Res.* 2017;70:338-45.

Kitchens B, Dobolyi D, Li J, Abbasi A. Advanced analytics for managerial decision support: a framework for big data analytics. *MIS Q.* 2018;42(1):161-82.

Chen DQ, Preston DS, Swink M. How the use of big data analytics affects value creation in supply chain management. *J Manag Inf Syst.* 2018;35(1):49-77.

Dubey R, Gunasekaran A, Childe SJ, Papadopoulos T, Wamba SF. The role of big data in explaining disaster resilience in

supply chains for sustainability. *J Bus Res.* 2017;70:239-46.

Fosso Wamba S, Akter S, Edwards A, Chopin G, Gnanzou D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *Int J Prod Econ.* 2017;185:234-46.

Ji-fan Ren S, Fosso Wamba S, Akter S, Dubey R, Childe SJ. Modelling quality dynamics, business value and firm performance in a big data analytics environment. *Int J Prod Res.* 2017;55(17):5011-26.

Pappas IO, Mikalef P, Giannakos MN, Krogstie J, Lekakos G. Big data and business analytics: a research agenda for realizing business value. *Inf Syst E-Bus Manage.* 2018;16(3):479-91.

Rialti R, Marzi G, Silic M, Ciappei C. Ambidextrous organization and big data analytics: a review and research agenda. *Technol Forecast Soc Change.* 2019;142:195-208.

Zhang Y, Ren S, Liu Y, Si S. A big data analytics-based approach for understanding the role of big data in supply chain management. *Technol Forecast Soc Change.* 2017;115:26-36.